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# ISSUES IN CAPITATION: RISK OF FINANCIAL RUIN FOR PROVIDERS AND WAYS TO CONTROL THIS RISK

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# CHAPTER ONE
# INTRODUCTION, PURPOSE, AND OVERVIEW

The purpose of this chapter is to provide an overview of research conducted for the Congressional Office of Technology Assessment under Contract Number 533-3220.0. This research considered general issues in capitation payment organized around the concept of the risk of financial ruin for providers and ways that this risk might be controlled. The chapter begins with a description of the problems associated with capitated payment and explains the rationale of the project as a whole. Next, the purpose of the project is described. The last sections are non-technical descriptions of Chapters II-VI, the technical core of the project.

## 1.1 PROBLEMS WITH CAPITATION PAYMENT

Capitation payment is one way to pay for an individual's health care expenses. It is one of a set of payment options that encourage providers to use resources efficiently by paying fixed amounts for bundles of individual services. Bundled payment subjects the provider to the risk that, if resource use is not controlled, the payment amount will be less than the provider's costs for providing the services. Note that the mechanism which creates the provider's incentives to efficiently use resources is the risk imposed on the provider by the bundled payment. Risk is created by the combination of bundling individual services into larger units of payment and paying a fixed amount for each unit.

For capitation payment, the unit of payment is one person year. An example of another unit is one treated case at a hospital; the payment unit for Medicare's Prospective Payment System. It is also important to note that the payment for the bundled unit must be fixed. Thus, for capitation, the provider receives one payment for all of the services covered by the capitation rate for one year.

The desirability of capitation payment in terms of the incentives it creates for providers has long been recognized. For example, in 1972 Congress created an agency within the Public Health Service to encourage capitated payment organizations. Medicare's early interest is indicated by the Capitation Demonstration Projects, first authorized in 1978. These projects were intended to demonstrate the problems of pre-paid contracting under Medicare.

Prior to 1982 Medicare lacked the legislative authority to enter into risk contracts with pre-paid health plans. The Tax Equity and Fiscal Responsibility Act of 1982 (TEFRA) changed this by providing a framework for Medicare to enter into risk contracts with eligible Health Maintenance Organizations or other competitive medical plans.

TEFRA also put strict limits on Medicare payments to hospitals on a per case basis. This limit system is the precursor to the Medicare Prospective Payment System. But why was prospective payment selected over capitation for Medicare? The reason was basic. There are, at present, too few organizations capable of handling the risk of accepting Medicare beneficiaries on a capitated basis. This is the first basic problem for capitation payment and one which raises two basic research questions. First, how effective are techniques that absolutely reduce the risk shifted from the program to the payee? Second, how does an organization's ability to bear risk change as the number of enrollees increases--is there an optimal size for an H.M.O.?

The second basic problem, called "cream skimming," is due to a potential inbalance in the information regarding a beneficiary between Medicare and an H.M.O. An H.M.O. can earn a profit in two basic ways. First, the organization can control its use of resources. This would hold costs, on average, to less than the payment amount. Alternatively, the organization could practice cream skimming by enrolling only those beneficiaries whose need for health care services are less than Medicare's average. This is the incentive for the capitated organization that may create problems for the payer.

This problem is, of course, recognized by Medicare in that Medicare rates are adjusted for the beneficiary's age, sex, institutional status, and welfare status. There are also separate rates for persons with end stage renal disease. The purpose of these adjustments is to control for the effects of biased enrollment, e.g., cream skimming, whether deliberate or by chance. These adjustments, however, account for less than three percent of the total variation in yearly cost per beneficiary. This means that if an organization can obtain information that predicts a beneficiary's need for health care services better than the prediction implied by the three percent variance reduction of the AAPCC, then it will be able to enroll persons who would have cost Medicare less than 95% of Medicare's average cost. This problem has led some analysts to fear that Medicare expenditures under risk contracts are greater than they would have been in the absence of such contracts--despite the fact that Medicare's payments are only 95% of the average for its beneficiaries in the local area.

The inability of current techniques to accurately predict a beneficiary's need for health care services can also work against the H.M.O. That is, the H.M.O. could enroll a biased sample of persons whose necessary treatment costs are expected to exceed the payment, irrespective of how efficient the H.M.O. really is. Thus, predicting treatment costs is important to protect both the program and the capitated organizations from the financial consequences of bias in the sample of persons enrolled. Research questions related to this problem include assessment of the relative usefulness of specific kinds of information in adjusting capitation rates, the effectiveness of different ways to use this information, and the effectiveness of other measures to control risk such as stop-loss reinsurance.

Adjustments to capitation rates may be concurrent or a prediction. Obviously concurrent adjustments would almost always be more effective than predictive adjustments in controlling for biased enrollment. However, the potential utility of the concurrent approach has never been seriously considered. This is because a concurrent adjustment process cannot provide incentives that are as powerful or as global for providers to use resources efficiently as a process based on predictions using only beneficiary characteristics. However, it seems reasonable to also consider options that, while imperfect, may be more acceptable to providers and/or options that represent a less dramatic change for the current health care delivery system.

Finally, it is of interest that capitation is almost always considered in terms of a payment for both ambulatory and hospital based care. The exception is the concept of a Social H.M.O., an organization that adds coverage of long term care to these benefits, thereby increasing the level of risk borne by the capitated organization. Since the willingness and ability of organizations to bear this risk is a serious issue, it would seem reasonable to also consider options that inherently transfer less risk to the payee. Medicare already has a prospective payment system (PPS) for hospital care. Therefore, capitation for Part B would seem to be an option worth considering, if only because this, combined with PPS, would create a complete payment system. Alternatively, if a PPS type payment system could be created for hospital based physicians, then capitation for ambulatory services might be a relevant option. This would be a three part payment system, complete as above, i.e., excluding only long term care. These options are closely related to the concept of concurrent adjustment noted above.

## 1.2 THE PURPOSE OF THIS PROJECT

The purpose of this project is to begin exploring the issues raised above. Specifically, the overall purpose is to examine the concept of risk for providers in a capitation payment environment and to estimate the effectiveness of various risk limiting techniques. The analyses are exploratory, and, therefore, should be taken as suggestions for further research. The following chapters contain fairly technical analyses of the areas described above. For the reader's convenience, a brief, non-technical description of the major conclusions of each chapter is provided next.

## 1.3 CHAPTER SUMMARIES

### Chapter Two "Risk Versus Variance"

The first step in this project was to establish a relationship between risk--a financial concept, and the statistical concept of variance. This was done by converting the variance to a probability that a provider would be ruined over a given time period. Ruin means that a provider's costs for one year exceed the provider's revenues for that year by more than a pre-specified amount. The important conclusions from this analysis are:

1. As providers' reserves increase, probability of ruin declines slowly.

2. Increasing variation in the cost of care greatly increases ruin probability.

3. If a particular formula reduces variation in treatment cost, this also reduces provider risk. A five percent

> reduction in variation (about AAPCC's level) in effect, increases the providers reserves by 2.5%. A 70% reduction in variance increases effective reserves by 82.6%. Of course, higher effective provider reserves mean that the probability that a provider will be ruined is reduced. Note that a 70% reduction would involve concurrent adjustment, and that about one half of this reduction would be related to knowing that someone had been hospitalized during the year.

From the provider's viewpoint, reducing variation in necessary expenditures per person translates to higher effective reserves; this reduces the probability that the provider will face financial ruin over any given time period. Since the inherent variability of per capita Medicare cut is high; variance reduction can be very important in capitating anything smaller than an area carrier. Increasing effective reserves by 50% requires a variance reduction of about 55%; increasing effective reserves by 100% requires a variance reduction of 75%.

Given these findings, it is necessary to examine the extent to which certain variables reduce variation. However, it is useful to note that a provider could be capitated for all Medicare (A & B), Part B only, or for ambulatory care only. The ability (and need) to reduce variation depends, in part, on the total variation itself. For providers, including hospital care costs in the capitation system adds variation, while paying for physicians and their associated services (Part B) alone exhibit less total variation--this ratio is about thirty-four to one. The combination (Parts A & B) is less than one half as variable as Part A alone. Thus, capitating physicians for Part B only (or some piece of these costs) is inherently much less risky than capitation that includes hospital costs. This is because the range of hospital expenditures for an individual can be extremely high, while physician cost variation is (relatively) more limited.

## CHAPTER THREE Controlling Risk: The Importance of Risk Factors and Stop-loss

The purpose of using certain factors (variables) to adjust capitation payment is to control for bias in enrollment. Bias in enrollment can occur only when a subset of the overall population is enrolled. That is, if a carrier enrolls all of the persons in a fairly large geographic area, biased enrollment is not likely to be a problem. In other circumstances biased enrollment is a risk for the provider. In addition, the potential for biased enrollment will exist if the capitation rates are not adjusted for factors that are strongly related to variation in necessary treatment cost. This means that HMO's will find that preselection for healthy enrollees (cream skimming) is a profitable strategy. Beneficiaries also may find that enrolling in inexpensive, low benefit plans is advantageous if they can reasonably expect to remain healthy. This phenomena is called adverse selection, and may damage high benefit, high cost plans. Thus, the purpose of adjusting capitation rates is to control for biased selection.

One way to assess the importance of risk factors is analysis of variance. A risk factor's importance will be different for Part A costs versus Part B costs. For Part A costs, the most important variable is mortality, followed by institutional status and age less than sixty-five. For Part B costs, diagnosis is most effective in reducing variation while institutional status, mortality and welfare are less effective. This is because death in a hospital can be a very expensive event, while an enrollee who dies uses more nearly the same amount of Part B services as one who survives.

If a stop-loss provision (a limit on the provider's losses per patient) is added to the capitation system, mortality declines in importance as a risk factor while institutional status and diagnosis increase in importance. This implies that mortality is associated in relatively few cases with extremely high costs. Since stop-loss reduces the effect of these cases, mortality becomes less important. Institutional status and diagnosis, unlike mortality, are consistently associated with higher treatment costs. Those costs are not isolated in a few extreme cost cases, but instead occur more generally.

Thus, the importance of specific variables depends on the costs under consideration and on the design of the capitation system itself. The effectiveness of the stop loss is striking, particularly in the A & B context. This is probably the most significant finding reported in this chapter. For example, a stop loss provision that pays 80% of charges above a $10,000 limit, reduces the variation in total charges (Parts A+B) by more than 60%.

## CHAPTER FOUR Controlling Risk In Capitation Payment: A New Grouping Technique and the Importance of Certain Variables

This chapter evaluates a pattern recognition technique called Grade of Membership to set capitation rates. A very important result of this research is that the Grade of Membership (GOM) grouping technique appears potentially superior to conventional methods in terms of reducing variation and thereby controlling risk. Comparing GOM to conventional groups using the same variables, the maximum possible variance reduction for Parts A and B using conventional techniques is 16.2%, compared to 63.6% using GOM. Both techniques in effect represent concurrent--not prospective adjustments, but at least half the additional variance explained by GOM must be attributed to the GOM model's "knowing" that someone was hospitalized. For Part B costs alone, conventional techniques can reduce variance by up to 26.3%; GOM reduces variance by 31.6%. In both these cases, GOM could do as well with less information, conventional techniques could not. The reason for this is that GOM combines discrete categories (the conventional technique) with a continuous adjustment process. Of course the absolute difference between the two techniques is smaller for the Part B charges where hospitalization is not "known" by the GOM model. (The word "known" appears in quotation marks because the fact of hospitalization was not included as a variable, but was *de facto* incorporated as a group definition.)

Assessing the importance of variables for GOM is somewhat different than the analysis of variance summarized above. GOM is a pattern recognition technique and variables that establish patterns will tend to be more important for GOM. This is why diagnostic information was found to be the most useful for GOM. Diagnostic information naturally forms patterns, the other variables were found to be parts of a pattern but were not patterns standing alone.

Finally, it is important to note that the explanatory power of concurrent adjustment using GOM (64% for A and B) is much greater than the predictive AAPCC (4%) or prior utilization

(5-10%) approaches. This suggests that the GOM pricing techniques represent an option worthy of serious additional research, perhaps with a potential for a demonstration in the not too distant future.

CHAPTER FIVE "Risk as Related to the Size of the Enrolled Population under a Capitated Payment System.

The argument for further exploring risk reduction techniques is strengthened by the finding regarding the optimal size. We found that there is a worst size for an HMO; between 50,000 and 100,000 enrollees--a common HMO size, but there is no "best" size. This implies that reducing risk is important if capitating these organizations is a program goal. These results also demonstrate that very large size is associated with lower risk. Therefore, large area carrier capitation is an option worth exploring and, perhaps, demonstrating. This result holds only if the H.M.O.'s reserves against financial loss have a relationship to enrollment size such as reserves being proportional to the square root of enrollment. This rule is not unlike the rules now used by insurance companies. It is also important to note that this finding relates to the H.M.O. as an insurer and refers only to its risk bearing function. H.M.O.s are also providers, and as such, should be expected to experience economies or diseconomies of scale for this function.

## CHAPTER SIX "An Evaluation of Three Payment Strategies for Capitation for Medicare"

The payment strategies chapter explores the effect on a provider's risk of ruin under three basic capitation models. The results are based on the assumption that either providers will be directly capitated or that carriers will be forced by competitive pressure to impose risk on providers via a DRG like approach to payment. Under these assumptions direct provider capitation is the lowest risk for providers. This is because anyone who bears risk must be paid a premium for so doing. In this model, only when the provider is directly capitated does the provider receive the entire risk premium. However, the gatekeeper insurer, i.e., an insurer who sends persons with specific conditions to specialists in those conditions would be preferred (in terms of provider risk) if the gatekeeper could control utilization by at least one percent. This means that, for providers, provider and gatekeeper capitation should be of real long term interest. Of course, this assumes that all providers could become adept at bearing risk, a function now performed only by providers such as H.M.O.s and other competitive medical plans. These provider based approaches might be explored in concert with capitation for Part B costs only since the absolute variation of these costs is lower than for Parts A+B.

The focus of this chapter on the risk of provider ruin as the sole criterion to evaluate one approach against another should not be taken as evidence that this should be the only or even the most important evaluative criteria. This one-dimensional focus is inherent in the process of mathematical modeling. The purpose of a model is to illuminate one aspect of a complex problem. As such, the technique is useful but limited in its applicability. Models such as the one developed and used in this chapter and elsewhere in this document may assist in the reasoned consideration of the problem, but they are not a substitute for the process of reasoning.

## CHAPTER SEVEN "Physician Practice"

An alternative to adjusting rates based on patient characteristics is to adjust rates based on physician practice characteristics. We were successful in identifying four distinct types (patterns) of physician practice. These were general practice, medical specialties, general surgery, and mental health specialties. Interestingly, these are the divisions that are at issue in the current discussions of fee schedules. Considering total Part B payments to physicians, this approach to adjusting rates represents a potential 75% reduction in variance. Thus, the utility of using provider type for adjusting payment, much as this is used under PPS, may be worthy of additional consideration and research. This is particularly true if capitating small entities (e.g., physician groups) for Part B only is to be made attractive for providers. This is not to suggest that the method or variables that we used for this analysis are appropriate for this task. Our purpose was to discover whether the potential for adjustments of this type existed, i.e., whether we could discover adjustments that reduced variance.

# CHAPTER TWO
# RISK VERSUS VARIANCE

## 2.1 INTRODUCTION

The purpose of this section is to define the concept of risk and illustrate its relationship with variance. As used here, a risk is a situation where the loss can exceed the capital (see Seal, 1967). The classic examples of the business of risk are life and health insurance. In either of these examples the insurer is at risk or liable to pay insurance claims that exceed his collected premium to date or the total premium he will ever collect from the insured individual. The insurance company must make up losses resulting from the realization of such risks from gains (unincurred claims) from other individuals. Note that this concept of risk is different than the idea of a "risky" venture or investment. If an investment is speculative or "high risk" then the investor may lose his entire investment. An insurance contract sold to an individual who is considered a poor risk may result in significant losses of capital not invested.

New trends in paying Medicare costs have also put hospitals and HMOs into the risk business. Both the prospective payment systems for hospital inpatient care and the per-capita payment plan under the risk option of the 1983 amendment to the Social

Security Act allow for the health care provider to lose more than "invested." Additionally proposed methods of reimbursing physicians for health care service to Medicare patients will also place the physician in the risk business. Since the risk business is fundamentally different than other business, it is essential that the concept of this risk be identified.

In a risk business the claim or amount paid by or lost to by the insurer or health care provider is random. Before an individual is actually given the health care required, even though a medical diagnosis is known, the actual costs to be incurred are unknown. The approximate cost for care or the costs one would expect to incur may be well guessed. However, the actual costs vary from this expectation for each individual for various reasons. Some of these reasons are differences in severity of disease, unforeseen complications, basic differences in individuals and so forth. Thus, thought the mean cost of care may be known, the actual cost for an individual will vary from this cost. The more individual costs bounce around the average, the more likely the health provider will accumulate larger losses. Thus, the extent to which these individual costs vary is related to the risk that the health provider takes if he is to be reimbursed only the average costs. Consequently, any reduction in the variation of the actual health care costs (claims) from that expected also reduces the risk the health provider takes.

## 2.2 VARIANCE AND RISK

As implied above, when a health provider enters the risk business he assumes the possibility of being ruined due to random chance. This random chance is the result of a bad run of luck resulting in an excessive number of claims exceeding the average. To get a feel for how the variance effects loss, we assume for now that the claims have a given mean, say $800, and that they vary about this mean according to the normal distribution of "bell curve." Figure 1 gives the probability that the health provider, who is reimbursed exactly the average amount, will have lost a certain amount at the end of one year of business. The x-axis is the amount lost measured in standard deviation units (s.d. units), and the y-axis is the corresponding probability. Thus, for example, if the variance was $10^6$ then the standard deviation, the positive square root of the variance, would be $1000. Thus the probability of incurring a net loss in the year of $10,000 (10 s.d. units) is approximately 2.5% (reading from figure 2-1). Note that this loss is cumulative and not simply the loss on one case. In other words, a $10,000 loss means the health provider will have worked the whole year and be $10,000 in the hole at the end.

By examining the graph in figure 2-1, we can see how a reduction in variance will reduce the loss for a year. If the variance were $2.5 \times 10^5$, then the standard error is \$500, exactly half the amount above. Thus a \$10,000 loss is now 20 s.d. units. Looking at the graph we see that the probability of losing \$10,000 in this case is nearly zero. On the other hand, if the variance were increased to $4 \times 10^6$, the standard deviation becoming \$2000, the probability of losses of \$10,000 or more, 5 s.d. units, is now about 8%. On the average, however, the health provider will have neither gains or losses at the end of the year.

Suppose that the health provider must never end a year with a loss of more than, say, $\$_x$. We assume that exceeding $\$_x$ causes the health provider to be "ruined" and that the probability of this event is independent from one year to the next. The latter assumption is less realistic than an assumption of dependence over time. However, profits and losses are carried over time. Thus, this illustrates the effect of long "runs" of good or bad luck.

Figures 2-2 and 2-3 depict the probability of being ruined sometime in the first 15 years and first 25 years respectively. The values of x recorded in these two graphs are in standard deviation units. For example, assume that the standard deviation is \$1000 (10 s.d. units) at the end of at least 1 of the 15 years is approximately 25%. If \$10,000 is the greatest loss the provider can absorb, then this is the probability of ruin. If the standard deviation was $500 (20 s.d. units = $10,000) this ruin probability of less than 5%. Similarly, a standard deviation of $2000 (5 s.d. units = $10,000) results in a ruin probability of over 55%.

Note that depending on the ruin level, the $10,000 loss limit above, the relationship between a change in the variance and the change in the probability of ruin differs. For example, looking at figure 2-3 if the ruin level is between about 8 s.d. units and 16 s.d. units, then a reduction in variance gives a large reduction in probability of ruin. On the other hand, if the ruin level is greater than 20 s.d. units the reduction in variance changes the 25 year ruin probability very little. Figure 2-4 gives a feel for how the ruin probability changes as a function of the number of years the health provider must avoid the loss and as a function of the ruin level.

Hence reducing variance at the level of the individual enrollee reduces the risk assumed by the insurer. There are two major techniques used by insurers so that risk will not cause the company to be ruined (loose more than a fixed amount of capital). These are:

1. Reduce the variability of the loss on any claim through
    a. Risk classification of individuals
    b. Use of reinsurance or coinsurance models.

2. To collect an extra amount, called the "risk loading," which build up a risk reserve.

The successful risk business would use both of these methods. The second technique is essential if the business plans on perpetual existence. We examine the use of these techniques in reducing the risk a health provider assumes.

One way to measure variance reduction is through a statistic called $R^2$. Generally, $R^2$ is interpreted as the variance explained by a variable or by a model. In the following we evaluate the goodness of a variance reduction scheme by using $R^2$. Here $R^2$ is the ratio of the amount of variance reduced by the scheme to the variance under no scheme. That is, $R^2$ is the variance explained by the scheme. A scheme which results in a reduction of variance, in effect, gives the health provider extra protection against ruin. Quantitatively, this extra protection is equivalent to increasing the ruin level of the health provider by $[(1 - R^2)^{-\frac{1}{2}} - 1] \times 100\%$. Table 2-1 gives the percent increases in the ruin level the health provider can tolerate as the $R^2$ increases, i.e., the benefit to the provider in terms of additional effective reserves under plans that reduce the initial variance by given amounts. As indicated in the table, the ruin level (provider's effective reserves) increases slowly at first, then rapidly as $R^2$ approaches 1.0. At 1.0, risk is eliminated; effective reserves are very large.

## 2.3 REDUCTION OF VARIANCE

Risk classification, one of the methods used to reduce variability of loss or claims, consists of a set of rules which determine if an individual has higher chance of incurring large claims. For example, one would expect an eighty year old male in a nursing home to have greater health care cost than a sixty five year old male living at home. Factors used to classify risk in the private health insurance industry include blood pressure, build, past history of medical problems, current health status and so forth. In Medicare risk classification scheme, more simply devised rules are used such as age, institutionalized status, end stage renal disease and welfare status. Under private insurance an individual classified as high risk may either be charged an extra premium or may not even be able to purchase insurance in the private market. However, under a social insurance program like Medicare, an individual can neither be denied or charged extra but the average amount paid to the health provider can be increased for high risk individuals.

For example, under the prospective payment system, the "risk" of an individual's health care cost is determined at the time he sees the health provider by classification into one of

469 diagnosis related groups (DRGs). To the extent this classification reduces the variance of cost, it also reduces the risk to a health provider reimbursed by DRG amounts. For capitation payment methods, the classification is intended to remove bias which can become a component of variance and risk. Exactly how these apply to our problem is reviewed below.

## 2.4 RISK CLASSIFICATION AND PROSPECTIVE PAYMENT

In this section we explain how the classification of individuals into relevant groups can be used to reduce risk. To do this we need the following notation.

$J =$ number of risk groups.

$n_j =$ mean claim amount for a person in the jth group.

$\delta_j^2 =$ variance of claim amount for an individual in the jth risk group.

$N_j =$ number of individuals from the population in the jth risk group receiving health care.

$N_T =$ total number of individuals in the population receiving health care.

$$= \sum_{j=1}^{J} N_j$$

From mathematical statistics we know that the variance of cost for a claim given a claim has occurred is

$$\text{Var Claim} = \sum_{j=1}^{J} \frac{N_j}{N_T} \sigma_j^2 + \left\{ \sum_{j=1}^{J} \frac{N_j}{N_T} \eta_j^2 - \left( \sum_{j=1}^{J} \frac{N_j}{N_T} \eta_j \right)^2 \right\}$$

The first term in this expression is the weighted sum of the variance for each of the risk groups, the weights being the relative proportion of the total patient population $N_T$ who are members of the risk group. The second and third terms, the two terms in brackets, are the weighted sums of squares of the means of the risk groups. The variance given above represents the total variability from the overall mean assuming that the amount reimbursed is the overall mean. If, however, the amount reimbursed for each patient is the mean of the particular risk group the patient was in, then the bracketed term is zero. This means that the total variance removable from the overall claim variance by paying different average claim amounts for the different risk groups is the total weighted sum of squares of the means of the group. For the prospective payment system this reduction is the measure of risk reduction provided by a risk classification. Naturally this risk reduction is totally eliminated if, for each patient, the overall average is paid rather than the risk group average.

Usually the risk groups are determined by the grouping of individuals by age, institutional and welfare status, and sex. Since we are dealing with reimbursements conditional on a claim--i.e., health care being delivered, one could also classify a patient by general disease group. The formula above provided a simple method of evaluating whether any of these risk factor variables such as, say, classification by welfare status, sex, etc., are worthwhile. Explicitly the weighted sums of squares accounted for by the particular risk factor variable when considered in an analysis of variance framework is equivalent to the amount of variance the factor can remove from the overall claim variance if used as a classification variable. Note that this analysis of variance is simply a computational device and does not require the usual assumptions of analysis of variance procedures.

Table 2-2 lists the overall variance and the variance accounted for by the following six risk factor groups. The risk factor variables defining these groups are:

1. Institutionalized or not.

   -A person was considered institutionalized if there was record of at least one nursing home payment.

2. Welfare or not.

   -An individual was classified as a welfare patient if there was a recorded state buy-in to Medicare.

3. Sex

4. Mortality.

   Whether a person died during the year or not.

5. Age: 65-74, 75-84, 85+, and under 65.

6. Major Diseases.

   a. Cancer
   b. Diabetes
   c. Major CVD
   d. Other $D_x$
   e. None

   -From inpatient and outpatient diagnosis codes. A person with multiple diagnoses was assigned to the group indicated by the first listed hospital diagnosis. If no hospital diagnosis was present, then the first outpatient diagnosis was used instead.

Table 2-2 also gives an $R^2$. Recall this represents the ratio of the total variance reducible by using the risk factor classifications to that of the total variability. How this changes the risk of ruin is given in Table 2-1.

## 2.5 RISK UNDER CAPITATION

In the preceding sections we noted the probability of ruin as a function of the variability in claim size or cost incurred for health provided to an individual. However, this analysis was conditional on an individual making a claim by receiving health care. Under the per capita payment payment, the health provider is given an amount for each individual enrolled whether they need health care in the year or not. This type or reimbursement strategy more closely resembles the classic health insurance model where the total capitation payment takes the role of a group insurance premium. The risks associated with this situation not only includes the variability in claim size but also the variability in the number who make claims.

Under this model if the average amount reimbursed does not exceed the average expected cost, the health provider will eventually be ruined. Therefore, in addition to the average per capita cost a small "risk loading" must be paid the health provider. There are several methods of fixing a risk loading. Here we will assume the loading is a small proportion $\varepsilon$ of, say, .01 or .02 of the expected per capita cost. Assuming $\varepsilon > 0$, then the ruin probability is bounded by the function

$$\exp \left[- \frac{2 \varepsilon n}{n^2+\delta^2}\right].$$

In this function n and $\delta^2$ represent the mean and variance of the annual claim amount. This bound is good for any distribution of claim size assuming that the claim count follows a Poisson probability law. Figures 2-4, 2-5, and 2-6 give the shape of this curve for various values of $\varepsilon$, and $\delta^2 = K_{\mu}^{2}$. The values are in units of the mean. (In other words if the mean is, say, $800, then each unit on the x-axis is $800). "K" relates mean costs to variance at the provider level. For the national sample the value of K ranged from 1 to 2 across providers.

We notice the happy result that this function does not involve the claim rate. Hence, given the values of n, K and $\varepsilon$, we can calculate the ruin probability for a health provider. Referring back to Table 1 for the variance, we can construct a table of ruin probabilities from figures 2-4, 2-5, or 2-6.

## 2.6 RISK CLASSIFICATION FOR CAPITATION

Consider the J risk groups introduced above. Let $M_j$ be the number of individuals enrolled in the cohort who are from group

$j$. Note that $N_j$ above is the number of these $M_j$ who make a claim during the year. Let $n_j$ and $\delta_j^2$ be the mean and variance of the cost of treatment for risk group $j$ and let $\lambda \equiv$ be the probability that an individual in group $j$ will require health care in the year. Here we continue to assume implicitly that the individual has either no visit or one visit per year. Naturally, many have multiple visits. This is accounted for in that $\mu_j$ is the average cost per year, not per individual visit. The reason for this assumption is that only annual cost data were available at the national level. Cost date from South Carolina, though, available at the individual provider level was not easy to separate into individual health events.

The mean and variance of the incurred cost for the capitation payment method expressed in terms of the risk groups are given by

$$\text{Mean Cost} = \sum_{j=1}^{J} \lambda_j \mu_j \qquad \text{Variance} = \sum_{j=1}^{J} \lambda_j (\mu_j^2 + \sigma_j^2)$$

It is important to note that the variance includes the term $\mu_j^2$. This is the man cost for factor group $j$ given that an individual form this group receives health care. Under the prospective payment scenario, these values are eliminated if the average cost in the factor group is paid at the time health care is received. Whenever the cost reimbursement is paid in advance, but not conditional upon an individual actually needing health care, the partitioning of the population into factor groups does not eliminate $\mu^2$. Hence, partitioning does not reduce variance at this point.

The reason for partitioning the enrolled cohort under a capitation scenario is to protect against bias in a sample of the total population. Explicitly if a health provider enrolls a subset of the population, the mean and variance of his costs are

$$\text{Subset Mean Cost} = \sum_{j=1}^{J} \lambda_j^* \mu_j \quad \text{Subset Variance Cost} = \sum_{j=1}^{J} \lambda_j^* (\mu_j^2 + \sigma_j^2)$$

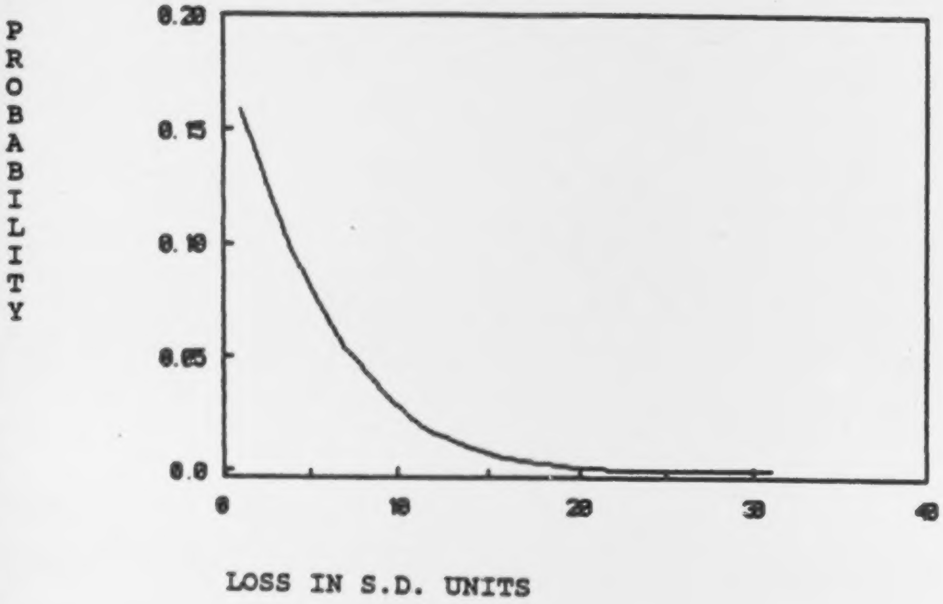
In these formulas the $\lambda_j^*$ values that is, the claim rate for the sample enrolled, are not necessarily equal to $\lambda_j$, the overall claims rate. In this case, depending on the values of $\lambda_j^*$, the health provider who is reimbursed an average amount calculated from $\lambda_j$, the overall average, will be reimbursed either more or less than the true average cost the health provider expects to incur. Naturally if he is underreimbursed, the health provider will be quickly be ruined. The ruin outcome is not a result of random variation in cost but the bias in the average cost due to the sample. If, however, the average cost reimbursed to the health provider is determined from $\lambda^*$, i.e., the providers claims rate experience, the reimbursement is "fair." If neither the population or enrolled cohorts are classified by risk groups in determining costs, then the estimated reimbursed costs are automatically based on $\lambda_j$.

The equation for the mean cost of the sample provides a mechanism for evaluating the effectiveness of a partition. Explicitly a weighted analysis of variance with weights $\lambda_j^*$ will determine which factors generating the partition are significant with respect to the enrolled sample. A factor, such as sex or welfare status, which, when eliminated has little effect on the explained variation ($R^2$) of the fitted model would have little or no effect on the reduction of sample bias mentioned above. If we were to assume for the analysis of variance that the weights $\frac{N_j}{N}$ are approximately proportional to $\lambda_j^*$ then the results given in Table 2-2 also apply to the evaluation of the partition.

We also see that the unexplained variability--the sum of squares of error is a measure of other potential bias factors not identified in the partition. But in other words, if there exists a large residual error in the weighted analysis of variance of the $\mu_j$ values, one might suspect another factor, not used in generating the risk groups to be lurking about. If this is true, health providers sampling an enrolled cohort and being reimbursed with capitation rate not using this lurking factor runs a risk of having a biased rate as noted above.

## FIGURE 2-1

### *VARIANCE REDUCTION AND THE PROBABILITY OF LOSS DURING ONE YEAR*

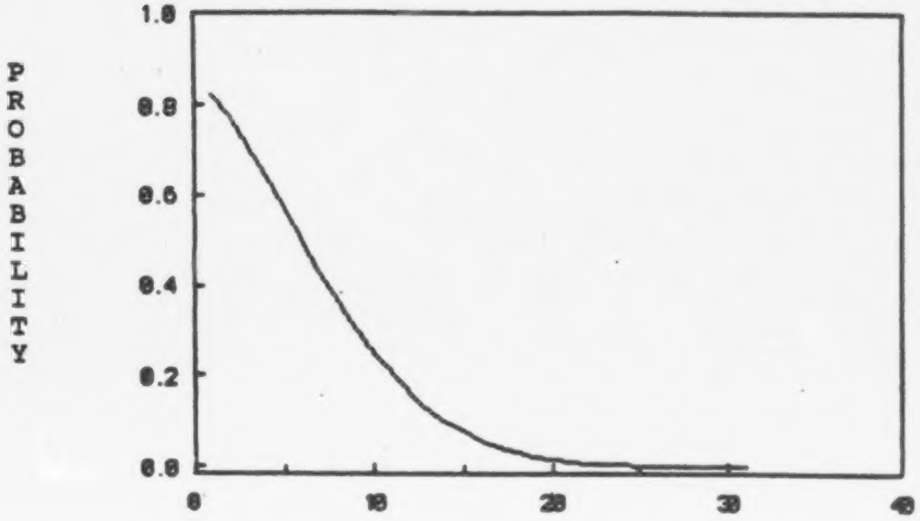


PROBABILITY OF LOSS AT END OF ONE YEAR

Note: If variance = $1,000,000; then S.D. = $1,000
When variance is reduced to $250,000; then S.D. = $500

## FIGURE 2-2

## *VARIANCE REDUCTION AND THE PROBABILITY OF EXCEEDING A SPECIFIC DOLLAR LOSS DURING FIFTEEN YEARS*



RUIN LEVEL IN S.D. UNITS*

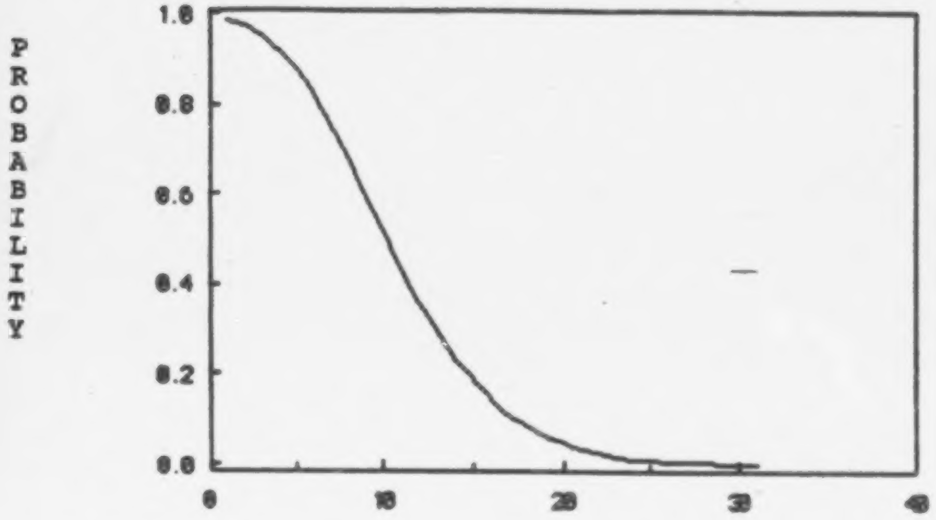
PROBABILITY OF BEING RUINED IN THE FIRST 15 YEARS**

Note: *Ruin level is equivalent to reserves required for the provider

**Ruin means that losses exceed a specified amount during the fifteen year time frame.

FIGURE 2-3

## VARIANCE REDUCTION AND THE PROBABILITY OF EXCEEDING A SPECIFIC DOLLAR LOSS DURING TWENTY-FIVE YEARS



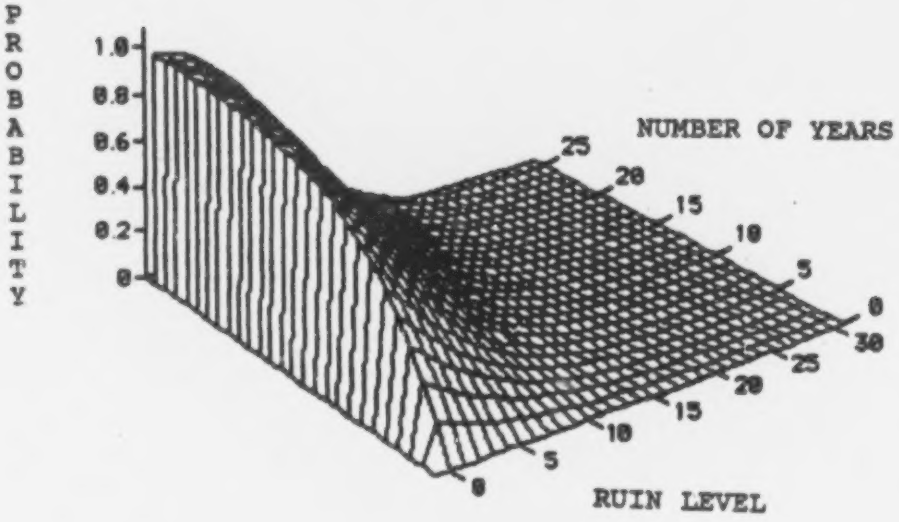
RUIN LEVEL IN S.D. UNITS*

PROBABILITY OF BEING RUINED IN THE FIRST 25 YEARS**

Note: *Ruin level is equivalent to reserves required for the provider
**Ruin means that losses exceed a specified amount during the twenty-five year time frame.

## FIGURE 2-4

## *VARIANCE REDUCTION AND THE PROBABILITY OF EXCEEDING A SPECIFIC DOLLAR LOSS PLOTTED AGAINST TIME*



## TABLE 2-1

## *PERCENT INCREASE IN RUIN LEVEL AS A FUNCTION OF $R^2$*

| $R^2$ | Percent Increase |
|---|---|
| .05 | 2.5% |
| .10 | 5.4% |
| .15 | 8.5% |
| .20 | 11.8% |
| .25 | 15.5% |
| .30 | 19.5% |
| .35 | 24.0% |
| .40 | 29.1% |
| .45 | 34.8% |
| .50 | 41.4% |
| .55 | 49.1% |
| .60 | 58.1% |
| .65 | 69.0% |
| .70 | 82.6% |
| .75 | 100.0% |
| .80 | 123.6% |

## TABLE 2-2

## *COMPONENTS OF VARIANCE OF CLAIMS COSTS FROM MEAN COST FOR CERTAIN SCENARIOS*

| FACTOR | PART A HOSPITAL | PART B TOTAL | PART A HOSPITAL AND PART B TOTAL |
|---|---|---|---|
| Total weighted $\sigma_1^2$ | 47,903,728 (89.8%) | 1140353 | 17,261,054 |
| Institution | 1,130,817 | 42733 (2.8%) | 453163 (2.2%) |
| Welfare | 25,732 (0%) | 2016 (.1%) | 120641 (.6%) |
| Sex | 120,067 (.2%) | 5034 (.3%) | 6170 (0) |
| Age | 40,958 (.1%) | 1041 (.1%) | 39967 (.2%) |
| Disease | 1,917,869 (3.6%) | 342418 (22.1%) | 2534892 (12.2%) |
| Mortality | 1,464,840 (2.7%) | 1 (0%) | 203890 (1%) |
| Residual | 730,451 (1.4%) | 18726 (1.2%) | 161117 (.8%) |
| Total variance | 53,334,462 | 1552319 | 20780894 |
| $R^2$ of Partition | 8.8% | 26.3% | 16.2% |

## FIGURE 2-5

*PROBABILITY OF RUIN, ONE PERCENT RISK LOAD, $u^2/\delta^2 = 1$*

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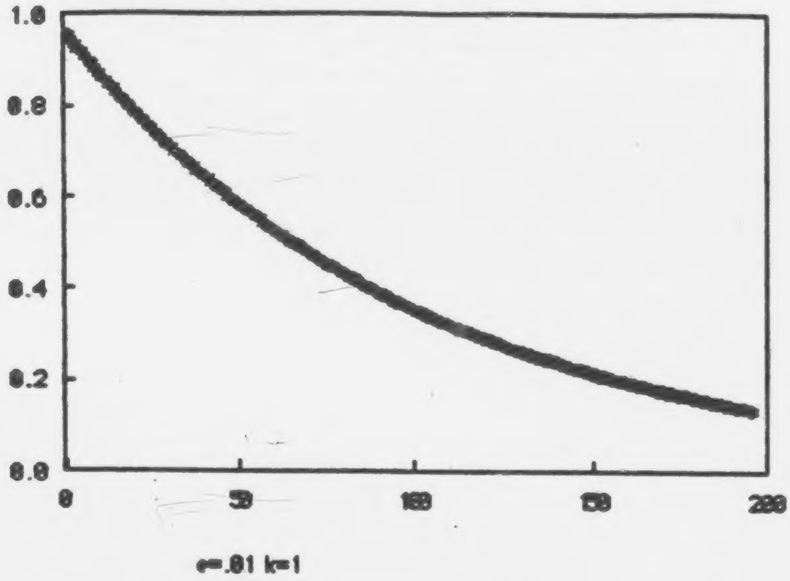

RUIN LEVEL IN MEAN VALUE UNITS

U = Logarithmic mean value

$\delta^2$= Variance of logarithm

FIGURE 2-6

*PROBABILITY OF RUIN, ONE PERCENT RISK LOAD, $U^2/\delta^2 = 2$*

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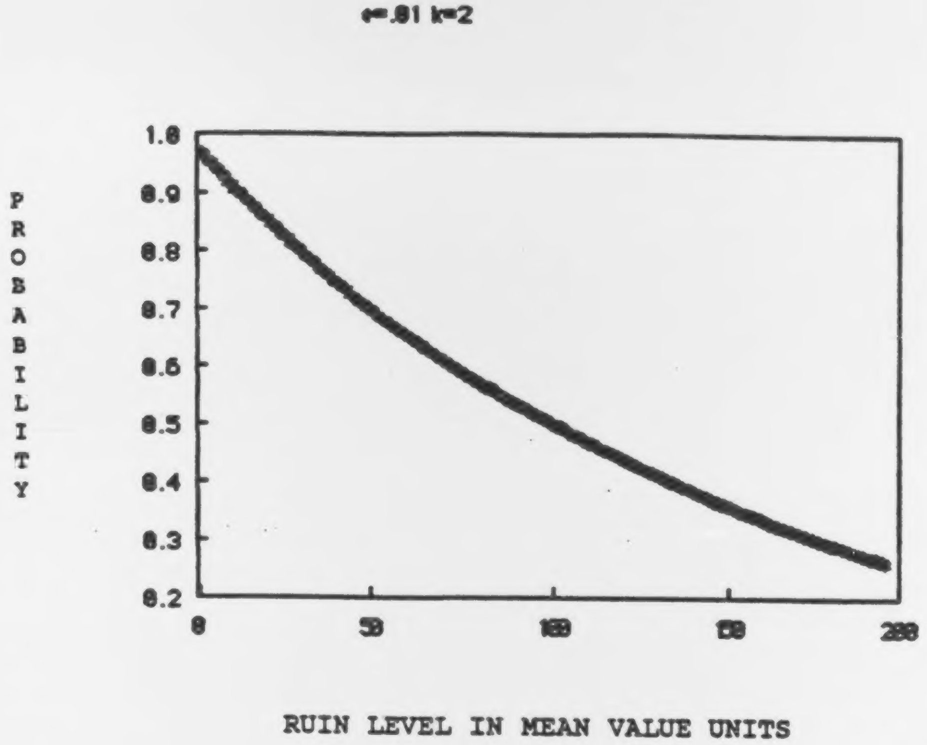
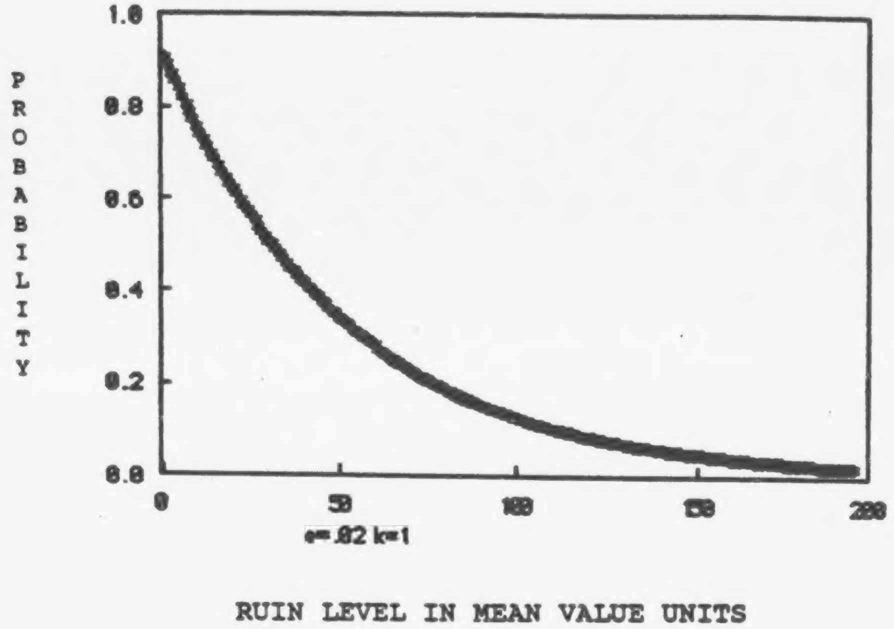


**$U$ = Logarithmic value**

**$\delta^2$ = Variance of logarithm**

## FIGURE 2-7

*PROBABILITY OF RUIN, TWO PERCENT RISK LOAD, $U^2/\delta^2 = 1$*

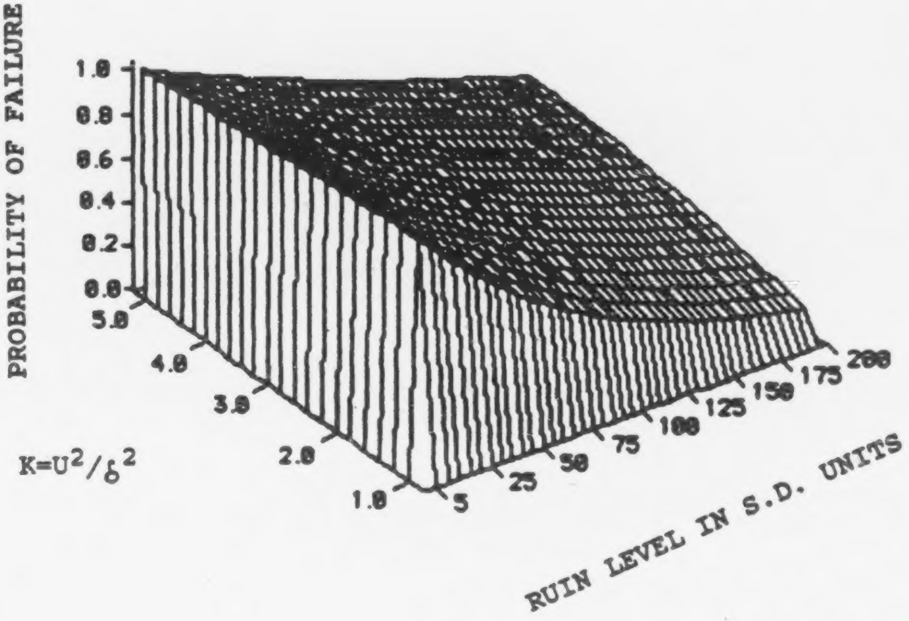


U = Logarithmic mean value

$\delta^2$= Variance of logarithm

## FIGURE 2-8

*PROBABILITY OF RUIN, ONE PERCENT RISK LOAD, $U^2/\delta^2$ VARIES*



# CHAPTER THREE
# BIASED SELECTION AND THE IMPORTANCE OF RISK FACTORS IN THE CONTEXT OF THE AAPCC

## 3.1 INTRODUCTION

In this section we will examine the relative importance of underwriting risk factors in the context of general capitation payment. Underwriting risk factors are those characteristics (variables) of individuals which are used to classify them into specific risk groups. Under a capitation payment schedule the number enrolled in each risk group determines the per capita rate for a provider. In the prospective payment schedule, an analogous situation exists. Here the payment for hospital care is based on the average cost for the risk groups as defined by diagnosis related group (DRG). Risk factors for DRGs are the patients' diagnosis, procedures, age, sex and discharge status.

Risk factor groups are used to control the provider's risk that a systematic bias in enrollment will lead to financial ruin. Therefore, the degree to which specific risk factor variables reduce the risk for the health provider is very important.

## 3.2 CAPITATION VARIABLES FOR RISK FACTORS

It is important to note that although both the capitation and prospective payment schedules use underwriting risk factors to determine costs, the risk factors are used in two distinctive ways. Underwriting risk factors for capitation are assessed for an enrolled group and are therefore restricted to risk factors thought to influence both utilization and cost. Prospective payment risk factors need only to account for utilization within a hospital stay. The AAPCC methodology uses the following variables as underwriting risk factors (Beebe et al., 1985).

1. End stage renal disease
2. Institutional status
3. Welfare status
4. Age, by category
5. Sex

Since end stage renal disease is known to be very costly, we will examine the remaining underwriting risk factor variables for individuals without end stage renal disease.

It should, however, be noted that if a health provider enrolls the entire cohort which was used to determine the costs for each risk factor group, then the classification by underwriting risk factor variables is unnecessary. This is because the role of the underwriting risk factors is to determine how similar the enrolled cohort is to the cohort on which capitation rates were made. In case of complete enrollment, biased selection can not occur. Similarly, a truly random sample of enrollees from this population, i.e., a sample which matches the base population, will have the same expected cost and the average capitation rate. Thus, the use of the underwriting risk factors for such a sample can not reduce either the variance of the sample or the risk to the health provider.

If, however, a health provider enrolls a cohort of individuals dissimilar to the base population then the capitation payment to the provider will need to be altered to allow for this biased selection. In this case, the reduction in risk due to biased selection is accomplished by correcting for any lack of similarity between the enrolled cohort and the base population regarding the number enrolled in each risk factor group in terms of expected cost. This correction should be dynamic, i.e., not only applicable to comparing the initially enrolled cohort to the population base, but also to adjust for the changing make-up of this cohort over time.

Underwriting risk factors are useful only if the risk factor groups they form truly reflect differential expected costs. This hypothesis that a particular variable is or is not useful in distinguishing groups that differ in terms of expected cost is the basis for judgment about the variable for capitation. One difficulty in examining this hypothesis for this study was that there is no count of how many individuals were in the various classifications but were not seen for health care. Our detailed data concerned persons who had health care expenditures. Since the utilization rates of the individuals in each risk factor group is not known, in order to evaluate the underwriting risk factors of the AAPCC of any other set of adjustment variables, the differential utilization rates were approximated.

More specifically, we assume that these utilization rates are proportional to the relative counts of individuals who received health care in each risk factor group. In this case the degree to which each underwriting risk factor protects against a bias selection, i.e., an unusual sample which results in erroneous capitation payments, is examined by analysis of variance. Table 3-1 presents this analysis for Part B charges based on a nationwide five percent sample of Medicare beneficiaries who incurred costs in 1981 or earlier.

The ANOVA output summarized in Table 3-1 assumes that the average Part B charge sampled from each risk factor group is approximately normally distributed, even though individual costs are probably more nearly lognormally distributed. This means that we tend to understate the utility of any given variable for adjusting capitation rates. The column of t-variables in Table 3-1 indicates the relative importance of the particular underwriting risk factor in guarding against biased selection. Any t-value in this column that is less than 2.5 in absolute values indicates that the factor is probably not important with respect to overall cohort costs. Table 3-2 contains similar results for part A hospital charges, part B total physician charges and part B other, non-physician charges. In both of these tables the costs are compared to the average for a non-institutional, non-welfare, female age 65-69 with no specific diagnosis in the year but receiving Medicare reimbursed health care.

To illustrate the results summarized in these tables examine the first t-value column of Table 3-1. The t-value for institutionalization is 13.27, much greater than 2.5. Thus, with respect to overall cohort cost, institutionalization is an important factor. Similarly, welfare status is also important. However, the low t-value for sex, .84, indicates that sex is not an important classification variable for determining overall costs. Recall, however, that the overall costs are relative to the frequency with which the risk factor variable occurs in the base population. We have not used any differential utilization rates. In our data this ratio is about 147:183 for males to females, respectively, for the sex variable. If the actual relative utilization in a cohort of males to females is different from this ratio, the sex factor may become important. Continuing down the t-value column in Table 3-1 we see that age under 65 is also important. In other words, the disabled population that is eligible for Medicare is not similar to the over 65 beneficiaries. Note that the t-values in this table are adjusted for any effect due to classification variables preceding them. Thus the age < 65 category has already been adjusted for the state-buy-in or welfare status variable, sex and institutionalization. Age groups for 70 and older show no sign of significantly affecting overall costs. Disease groups, on the other hand, show a strong relation to costs as does mortality outcome.

In interpreting the t-value column one should keep in mind that this is a measure of the importance of the particular classification factor relative to the overall cost for the base cohort. A classification which has an average cost much greater than the rest but occurs very infrequently may not contribute "significantly" to the overall costs. Thus, it would have a small t-value. Nevertheless, an increase in the enrollment of the number of individuals in such a classification might greatly effect the financial solvency of the health provider. The second t-value column measures the significance of the particular classification variable with respect to each individual. A t-value in this column less than 2.5 in absolute value indicates that the classification variable is not important for any individual. However, some variables may have appeared important overall in the previous t-value column and not important in this column because of the relative number of individuals in each level of the classification. The fourth column gives the mean value associated with this second t-value. Each individual who needs health care will have an expected cost equal to this value in addition to the overall mean. Consequently, these mean values indicate how much a change in the number of individuals at each level of classification will change the cost for the cohort.

As an illustration of how to use columns 3 and 4, we consider only total part B costs (Table 3-1). The grand mean is $1,001 meaning that on the average total annual Part B charges for a female 65-69, non-institutionalized, non-welfare with no diagnosed disease will be $1,001 given that the individual receives Medicare reimbursed health care. Table 3-3 lists the utilization rate of Medicare patients from 1975 to 1977 as given in Gresch and Leong (1983). From Table 3-3 we see that the probability that a 56-59 year-old female will have a Medicare claim in the year is .5249. Hence, the expected costs for each female non-institutionalized, non-welfare is 1001x.5249 = $525. Note, however, that if an individual has a Medicare claim, and also has cancer during the year, the cost estimate must be incremented by $1,781. The $525 is the per capita payment and the $1,781 is the expected additional cost for an incoming female with cancer.

If the individual was a non-institutional, non-welfare male age 70-79 with no diagnosed disease but with Medicare reimbursable health care expenses, then the expected average cost is the sum of $1,001 (grand mean) plus ($-45)(male) plus ($-259)(age 70-79) which equals $697. From Table 3-3 we see that the probability the individual has a claim is either .5419 or .5749, depending upon whether he is in the 70-74 year age group or the 75-79 age group. Assuming the latter, the per capita costs would be $697 x .5749 = $401. The per capita cost estimate does not assume the individual has Medicare costs in the year. If he does and it turns out he has a diagnosed disease (but not cancer, diabetes, or CVD), then the health provider can expect $862 in additional costs.

Neither disease classification or mortality outcome are generally used as classification factors in advance, i.e., as predictors (It may be worthwhile to examine the utility of certain chronic diseases as predictors. This is a complex issue because one would expect chronic and acute disease episodes to interact). These factors (disease and mortality) can be used as viable underwriting factor variables under either of two scenarios: 1) adjustment in enrolled cohort profile over time and, 2) use of the 'case manager' model. The first of these models is proposed in Tolley and Manton (1985) regarding the concurrent adjustment of the AAPCC rate for HMOs using mortality patterns. The second of these is, in part, illustrated in the examples above and is discussed more fully in a separate paper.

## 3.3 PROSPECTIVE PAYMENT BIAS

Use of underwriting risk factors for prospective payment schedules is important for two reasons; avoiding sample bias and reduction of cost variability. Similar to the above discussion, the use of factors which classify the individual by expected costs can protect the health provider from sampling bias. If the distribution of underwriting risk factors across individuals who require health care (not just the enrolled as above) differs from that of the base population on which average costs were calculated, expected incurred costs will be different from the base population average. Consequently, if the prospective payment does not adjust for underwriting factors, the health provider will not be reimbursed the correct amount. The extent to which failure to use an underwriting factor can bias the expected incurred costs are also given in Tables 3-1 and 3-2 for annual costs per individual.

To illustrate an extreme case, suppose that no risk factor was used in determining the amount to be paid. Put in other words, the overall average is paid the health provider for each patient. This average in the Medicare 5% sample data we analyzed for total Part B charges was $771. This average is the result of the mean values given in Table 3-1 weighted according to the relative frequency of occurrence. For example, the relative frequency of Part B charges in the same data by disease type was 29:10:91:193:618, respectively, for cancer, diabetes, CVD, other diagnosis and no diagnosis. Suppose that the health provider had more cancer patients and less CVD patients. From Table 3-1 we see that differential cost is $1,781 - 1,002 = $779. Thus each extra individual (with respect to this frequency) that is a cancer patient rather than a CVD patient who has reimbursed Medicare costs will be expected to incur an amount of $779 annually over the amount the health provider is being paid. Note that the health provider is only being reimbursed $771, regardless of disease. However, over the year, on the average, he will make up the differences due to the number of patients whose costs are over and under this amount, provided the relative frequencies match the base population. The $779 loss per individual cancer patient who receives health care instead of a CVD patient represents the amount per patient the health provider will not be able to make up. This loss is because of a shift up in relative frequency of cancer patients and a corresponding shift down in the frequency of CVD patients.

Looking at Table 3-1 it is clear that enrolling younger patients, i.e., the disabled, does not lower cost. If a provider could control the profile of patients served, while being reimbursed the overall average, then the health provider would stand to gain a great deal. Use of underwriting risk factors eliminates this gaming opportunity while protecting health providers who have disproportionate numbers of expensive patients. Thus, they protect the Medicare program against "cream skimming," and providers against adverse selection.

## 3.4 MORE SOPHISTICATED UNDERWRITING FACTORS

There are at least two major alternatives for constructing a reimbursement model that can reduce the financial risk to the health provider and reduce the likelihood of bias in the estimated payment rate. These are 1) use of a stoploss methodology, and 2) application of the grade of membership (GOM) model for determining risk factors.

Stop-loss is a form of reinsurance. It protects against expenditures above a certain level. For example, in the capitation context, a stop-loss provision might be: the reinsurer covers 80% of all costs per person in excess of $10,000 per year. This concept of stop-loss is analogous to the cost outlier provision in Medicare's prospective payment system (PPS). Under PPS, Medicare will pay 60% of per case costs in excess of $10,500 (in 1985), or twice the DRG rate, whichever is greater. The purpose of a stop-loss provision is to reduce the risk for a provider that a particular case results in large losses. The purpose of this section is to evaluate the effectiveness of a stop-loss provision of this type in reducing risk under three capitation scenarios. These scenarios are:

1. Part A - Capitation to hospitals for all Part A payments.

2. Part B - The physician is responsible for all physician payments and all ancillary service use. No hospital payment is included.

3. Parts A Plus B - HMO - The HMO is responsible for providing all Medicare benefits at a fixed rate per person per year.

Stop loss provisions can be effective in reducing risk when there are a few very high cost persons in a cohort of more nearly average people. This is an accurate description of the total costs of care for Medicare eligibles--most people incur costs at or under the average and a few people incur very high costs in one year. This is really what is meant when Medicare costs are described as "lognormally" distributed.

Table 3-4 gives the mean value and t-value for the per person costs under a stoploss reimbursement schedule for some of the charge categories given in Tables 3-1 and 3-2 (The technique used to derive Tables 3-4 and 3-5 is described in Appendix B). Note that under stoploss, the health provider must still make up 20% of the costs in excess of the limit. For this reason, the tables assume no increase in utilization due to the presence of stop-loss. In Table 3-4 we have set the limit at $10,000 for total Part A hospital and $5,000 for Part B charges. To control biased selection within the stop-loss framework, these levels would need to be different for each risk factor group. Comparing with Tables 3-1 and 3-2, we see the mean values are shifted down consistently but not by a large amount. Thus we see that the extreme tail of the distribution, in other words, the very costly patients, accounts for a small portion of the average costs, but a large proportion of the variance or risk associated with extreme costs. The conclusion is that the use of stoploss greatly reduces risk with only a moderate loss in revenue (assuming that payments are reduced by exactly enough to pay for the stop-loss protection) for the health provider. With regard to the Medicare program, this unpaid revenue, i.e., the reduced payments, exactly matches the additional expense Medicare incurs by paying the stoploss amount.

Table 3-5 presents the reduction in variance of stop-loss provisions in which Medicare pays 80% of charges in excess of $5000 and $10,000 per person respectively, for the three scenarios described above. From this table it is evident that for charges that may be very large, i.e., parts A and A plus B scenarios, a stop-loss provision can reduce variance, and therefore risk, dramatically. The smallest reduction for these categories is 62.5%. For these scenarios, the $10,000 level provision seems to do most of the work. Part B charges exhibit the infrequent but extremely high levels per year associated with the above two scenarios but to a lesser extent. Thus, a stop-loss provision set at $10,000 is less effective for these costs. Here the $5000 level provision seems most effective, increasing the variance reduction from 13.0% at $10,000 to 32.3% at $5000.

As noted earlier, if the Medicare program acts as the reinsurer, the stop-loss provision does not represent an additional cost. The capitation rates could be lowered by enough to pay for these cases. Actually, since these provisions reduce risk so dramatically, the loading added by an HMO to the rates it needs to obtain to remain viable might be lower as well. Thus, the lowest capitation rate with stop loss can be still less because the necessary risk premium can be lower. Thus, stop-loss provisions can actually save money. Of course this is only true if the government is the reinsurer. Since a government cannot be ruined, no risk premium is associated with the government filling this role. If, however, a private reinsurer is used instead, the provision cannot save money for Medicare. In this case, total risk is conserved; the reinsurer simply accepts part of the risk and attaches an appropriate risk premium for so doing.

We should note that a patient level stop loss would require the HMO to produce dummy claims for each enrollee that received services. The alternative would be to provide stop-loss protection at the plan level. This option would require HMOs to provide cost reports. the plan level option would provide more protection to fewer plans than the patient level model, and reduce overall variation by a much smaller amount.

The second suggested method of reducing variability is the GOM model. In this paper we have discussed underwriting risk factors as explicit classification variables; and individual was in one class or another. The grade of membership model allows each person to define his own classification according to his similarity with respect to certain underlying pure type classification variables. The GOM procedure is explained more fully in another paper. The major drawback in the use of GOM models is that some of the variables which are used to classify individuals are not known a priori. Therefore, the GOM model based on these variables cannot be used to predict a capitation payment. This is the same problem noted above regarding the use of mortality as an underwriting risk factor. However, methods of indirect modeling and adjustment would allow one to supplement capitation estimates prospectively with a GOM model. Unfortunately, pursuing this concept is beyond the scope of this project.

Table 3-1

*Analysis of variance results for total Part B charges. The t-value measures the importance of the factor in determining overall costs for Medicare Beneficiaries with reimbursed Part B charges.*

| Underwriting Risk Factor* | Cohort t-value | Individual t-value** | Mean*** |
|---|---|---|---|
| Grand Mean | | | 1001 |
| Institution | 13.27 | 12.57 | 894 |
| Welfare | 9.03 | 1.72 | 115 |
| Sex | .84 | -.68 | -45 |
| Disabled | 6.46 | 1.01 | 108 |
| Age 70-79 | 1.70 | -2.45 | -259 |
| Age 80-89 | 2.61 | -5.46 | -576 |
| Age 90+ | 1.68 | -9.28 | -982 |
| Disease Cancer | 55.67 | 13.94 | 1781 |
| Disease Diabetes | 15.23 | 8.06 | 1030 |
| Disease CVD | 52.01 | 7.85 | 1002 |
| Disease Other | 52.19 | 6.76 | 862 |
| Mortality | 9.45 | -2.93 | -196 |

*Each factor is net of the influence of all factors entered earlier.

**Unweighted t-values to measure importance of mean value in calculating cost per individual.

***Equivalent to the coefficient of a dummy variable in an OLS regression.

Table 3-2

Analysis of variance results for Medicare Charges. The t-value measures relative importance of the factor for determining overall costs.

| Underwriting Risk Factor | Part A - Hospital | | | Part B - Physician | | | Part B - Non-Physician | | |
|---|---|---|---|---|---|---|---|---|---|
| | t-value | t-value* | mean | t-value | t-value* | mean | t-value | t-value* | mean |
| Grand Mean | | | 2065 | | | 796 | | | 911 |
| Institution | 15.70 | 14.20 | 4165 | 12.96 | 13.12 | 713 | 11.86 | 10.94 | 741 |
| Welfare | 3.62 | .29 | 83 | 6.94 | 1.32 | 68 | 8.66 | 1.63 | 104 |
| Sex | .02 | .62 | 180 | 1.18 | .16 | 8 | .99 | -.31 | -20 |
| Age < 65 | 6.39 | .32 | 147 | 5.40 | -.43 | -35 | 6.03 | 1.07 | 108 |
| Age 70-79 | .51 | -2.96 | -1334 | 1.81 | -2.57 | -207 | 1.38 | -2.50 | -251 |
| Age 80-89 | .29 | -5.99 | -2729 | 2.59 | -5.86 | -472 | 1.35 | -5.56 | -559 |
| Age 90+ | -.22 | -9.45 | -4344 | 1.26 | -10.05 | -813 | .17 | -9.29 | -936 |
| Disease Cancer | 1.53 | 7.07 | 6681 | 52.43 | 15.87 | 1548 | 58.10 | 14.54 | 1768 |
| Disease Diabetes | 1.05 | 6.25 | 5909 | 16.28 | 10.13 | 989 | 15.53 | 8.09 | 985 |
| Disease CVD | 1.29 | 6.22 | 5878 | 56.14 | 9.85 | 960 | 52.98 | 7.78 | 945 |
| Disease Other | .59 | 5.42 | 5124 | 56.21 | 8.39 | 818 | 54.24 | 6.87 | 835 |
| Mortality | 30.13 | 8.77 | 2560 | 8.39 | -2.43 | -124 | 9.20 | -2.50 | -160 |

*Unweighted t-values to assess importance of mean value in calculating cost per individual.

Table 3-3

Including rates--probability an individual will need health care (Part B) during a year.  Note different age group break down for older elderly.

| | | Age | | | | | |
|---|---|---|---|---|---|---|---|
| | | <65 | 65-69 | 70-74 | 75-79 | 80-84 | 85+ |
| Sex | Male | .4689 | .4828 | .5419 | .5749 | .5875 | .6120 |
| | Female | .57464 | .5249 | .5788 | .6105 | .6274 | .6332 |
| Total | | .5085 | .5060 | .5632 | .5968 | .6132 | .6264 |

Source:  Gresch and Long, 1983.

Table 3-4

**Analysis of variance results for medicare costs under 80% stoploss.**

| Underwriting Risk Factor | Part A - Hospital ($10,000 Limit) | | Part B - Total ($5,000 Limit) | | Part A Host & Part B Total ($10,000 Limit) | |
|---|---|---|---|---|---|---|
| | Mean | t-value | Mean | t-value | Mean | t-value |
| Grand Mean | 1768 | | 872 | | 528 | |
| Institution | 2464 | 18.04 | 763 | 12.82 | 1536 | 17.75 |
| Welfare | 170 | 1.25 | 104 | 1.86 | 84 | .98 |
| Sex | 51 | .38 | -43 | -.77 | -9 | -.11 |
| Age < 65 | 138 | .65 | 75 | .84 | 150 | 1.12 |
| Age 70-79 | -541 | -2.57 | -184 | -2.08 | -358 | -2.69 |
| Age 80-89 | -1213 | -5.73 | -435 | -4.93 | -872 | -6.49 |
| Age 90+ | -2016 | -9.42 | -787 | -8.88 | -1560 | -11.49 |
| Disease Cancer | 4638 | 10.54 | 1588 | 14.85 | 4117 | 14.76 |
| Disease Diabetes | 4118 | 9.37 | 965 | 9.02 | 3505 | 12.57 |
| Disease CVD | 3989 | 9.07 | 923 | 8.68 | 3410 | 12.23 |
| Disease Other | 3354 | 7.62 | 840 | 7.86 | 2969 | 10.64 |
| Mortality | 1432 | 10.55 | -142 | -2.53 | 606 | 7.05 |

Table 3-5

*Reduction of Variance for 80% "Stop-Loss" at $5000 or $10,000 per Year*

| Reduction in Variance at | Part A | Part B | Part A & Part B |
|---|---|---|---|
| $5000 | 79.8% | 32.3% | 88.5% |
| $10,000 | 62.3% | 13.0% | 73.5% |

# CHAPTER FOUR
# CONTROLLING RISK IN CAPITATION PAYMENT: A NEW GROUPING TECHNIQUE AND THE IMPORTANCE OF CERTAIN VARIABLES

## 4.1 INTRODUCTION--THE PROBLEM

Capitation payment is of increasing interest to policy makers at both the Federal and State levels because this type of payment gives providers global incentives for efficient use of resources. These incentives are created by financial risk. Specifically, if an HMO cannot use resources efficiently, its costs may exceed payments and it will be ruined. The concept of "risk," however, has two separable meanings. There are risks due to unavoidable random variation in necessary treatment costs, and risks due to systematic variation in necessary treatment costs. Systematic variation means that the observed variation in treatment costs is causally related to a specific variable/characteristic/risk factor. The characteristics which might be related to variations in cost may be divided into four major categories. These are:

1. Beneficiary characteristics, e.g., age, sex, type of diagnosis, welfare status, etc..

2. Treatment characteristics, e.g., institutionalized, had surgery, prior years utilization of Medicare services, hospitalized, saw a physician, etc..

3. Provider characteristics, e.g., specialist physician, teaching hospital, public clinic, for-profit ambulatory surgical center, etc..

4. Environmental characteristics, e.g., local wage levels, population density, degree of local competition for Medicare patients, SMSA size, etc..

As a general proposition, adjusting capitation rates to reflect one of these characteristics will reduce the bias in treatment cost faced by a provider. In addition, if the adjustment is concurrent (i.e., is not a prediction), the potential reduction in variation bias can be larger because no prediction error could be involved. Since risk is related to variation, an adjustment can reduce the risk of enrolling an atypical population, and (cet. par.) increases provider acceptance of the system. However, the purpose of a capitation system is to create incentives, and incentives are only created through risk. The goal in designing a capitation system is not to maximize explained variation, but instead, to seek a balance between provider protection and the transfer of risk in a given payment context. Next, we describe a method which uses information like that categorized above to define types of people based on patterns present in the information.

Systematic variation can result in several types of problems for an unadjusted capitation payment system. One general class of these problems stems from unbalanced information, e.g., a Medicare eligible may be better able to estimate his/her future health care expenditures than the program or an HMO. For example, the beneficiary might be aware of certain signs or symptoms or might interpolate from family history, or otherwise use information that is not available to the other parties. If we assume an unadjusted voucher type payment system where the beneficiary pays a premium over the voucher amount to purchase more comprehensive benefits, and if this information inbalance exists, then adverse selection may become a problem. In this case, adverse selection occurs because beneficiaries who believe they will not require many health care services have an incentive to select inexpensive (low benefit) plans, while beneficiaries who expect high expenditures (or who are risk adverse) select the more costly high benefit plans. If the beneficiaries' predictions are accurate, the high cost plan will become more costly while the lower cost plan will become still lower cost. These are the consequences of adverse selection, and, therefore, the potential consequences of inbalanced information at this level.

Another potential inbalance of information occurs between the Medicare program and capitated organizations, e.g., HMOs. In this instance, the HMO might have or be able to obtain more information about a particular potential enrollee than the program has available. The HMO could use this to "cream skim," i.e., to enroll only persons who are likely to require few medical services during the coming year. If Medicare pays the HMO a rate per enrollee based on Medicare's overall average cost per person, the HMO can profit through cream skimming. This is one reason that offering HMO enrollment as an option for Medicare beneficiaries may actually increase program spending.

## 4.2 PURPOSE

The purpose of this paper is to describe and evaluate one potential solution to the problem of inbalanced information. In essence, to ameliorate this problem one needs to predict an enrollee's health care costs or to adjust the capitation payment concurrently for factors that influence resource use. Of course either of these techniques may be used in combination with techniques that actually reduce the total amount of risk shifted from the Medicare program to an individual provider. Examples of payment system design factors that accomplish this purpose include stop-loss insurance provisions and capitating for a less variable subset of Medicare costs such as Part B costs alone.

In any event, the issues related to predictive or concurrent capitation rate adjustments may conveniently be divided into two parts. The first involves how the information to adjust the rates will be used. We present in the following sections a new technique for computing adjusted rates. We believe that, because this pattern recognition technique is much more powerful than the current technology, it offers great promise for capitating relatively small organizations or areas. The second issue involves the utility of various kinds of information for adjusting capitation rates. This issue is evaluated in terms of the utility of the information for the pattern recognition technique. We conclude with a brief discussion of the relationship between incentives for efficiency and the kinds of information used to adjust the capitation rates. It is important to note that results will depend on the basic payment system under consideration. In this paper we will consider three capitation payment scenarios. These scenarios are:

1. The Health Maintenance Organization (HMO) Model. Capitation rates include all of Medicare Parts A and B. While capitation for Parts A plus B will be referred to herein as the HMO model, these results apply whether an HMO, a physician, or an intermediary actually receives the rates. In other words, these results do not depend on the number of people enrolled.

2. The Part B Model. Capitation rates include inpatient physician, outpatient physician, and all outpatient ancillary services.

3. The Case Manager Model. Capitation rates are limited to outpatient physician and outpatient ancillary services. The case manager pays other physicians, pays for all outpatient tests and procedures, and must authorize a hospitalization. However, the case manager's liability ends at the hospital door.

## 4.3 A DESCRIPTION OF GRADE OF MEMBERSHIP

The Grade of Membership (GOM) model is a pattern recognition technique. It is based on a kind of grouping theory called "fuzzy set" classification. Most grouping techniques create groups where an individual is a member of group one or group two or group three, etc.. Groups of this type are called fixed boundary groups. For example, the AAPCC risk categories used by HCFA are fixed boundary categories--an individual is in a certain age range, is or is not institutionalized or on welfare, is male or female. AAPCC groups are formed by cross classification using all of the AAPCC variables. Thus, one such AAPCC group would be institutionalized sixty-five year old males not on welfare located in a particular county.

GOM is different from conventional fixed boundary groups in four important ways. First, GOM's groups are more like pure types or archetypes than actual groups. We may find, for example, that one pure type is old, has several diagnoses, was probably hospitalized during the year, and is very costly to treat. Second, each individual is allowed to belong to more than one pure type. In other words, an individual will be assigned a grade of membership in several pure type groups, e.g., 25% pure type one, 30% pure type two and 45% pure type three. These scores will later be used to compute prices for the pure type groups. The third important way that GOM differs from other grouping techniques is that it is based on maximum likelihood statistics. This means that its groups produce valid statistics, and implies that one may generalize from a sample to the population with little loss of information (shrinkage). In this analysis shrinkage was less than two percent. Fourth, GOM statistics can be used to determine the appropriate number of groups--a serious problem for other grouping techniques. This property is described in the more technical discussion of GOM in Appendix A.

## 4.4 THE DATA

The data used for this analysis are for South Carolina, calendar year 1981. The Part B data were collected from the carrier and are of particular interest because they contain a two digit outpatient diagnosis code. These data also allow separation of inpatient and outpatient physician charges.

Part A and demographic data are from the Medicare data system. These data cover all persons who had Medicare covered charges in 1981. As with all data containing information that was not used for payment purposes, data quality is open to question. This is particularly true for diagnostic information. Both the Medicare and carrier data contained information on charges, not costs. Of course, information from a single state may be biased relative to more nationally representative data. The following results should be interpreted with these caveats in mind.

## 4.5 METHOD

In order to assess the utility of additional information while still utilizing the pattern recognition power of GOM, variables from these data were entered sequentially. In other words, four separate sets of GOM groups were produced. The groups in table 1 are from the last computer run including all variables. The earlier groups are not included due to space considerations. The first set of variables are outpatient diagnoses (numbers 1 to 21 in Table 4-1). The second set added inpatient diagnostic information (numbers 22 to 49 in Table 4-1). Third, since prior research (see Tolley and Manton, 1985) indicates that death may be an important factor in judging cost, this information was added to the grouping variables--(Variable 51). Finally, in step four, variables used in the AAPCC, welfare status, sex, and age were added. Here welfare status means that the state paid the individual's Part B premium (state buy in).

Table One also includes total cost. GOM allows one to examine variables like this (i.e., it produces the relevant set of statistics) without actually using the variables to create the pure type groups. The three groups on Table One were formed from all of the information except the cost information. In a later section we will evaluate whether all of this information was really needed. First, however, it will be useful to review the three pure types presented in Table 4-1.

## 4.6 RESULTS FOR THE PURE TYPE ANALYSIS

The first step in such a review is to note that four groups were evaluated. That is, three groups were compared to two and to four groups. Four groups did not appreciable alter the likelihood/ratio ($t = 1.161$)--the additional group provided little gain in information. This was true for the three earlier sets of groups created from each of the four sequential data sets described above. That is, only three pure types are needed to describe these data. More precise and detailed information would, almost certainly, allow formation of additional groups.

The second step in reviewing the pure types is to examine the four columns in Table 4-1. The first column gives the probability of observing this event in the population. For example, 4.8 percent of the cases in our data had an outpatient diagnosis of infectious disease.

The remaining three columns give the probability that this event will be observed in each of the three groups--3.97% for group one, 14.14% for group two, and 0.0% for group three. In other words, infectious disease is a characteristic of group two. Death occurred in 7.65% of the cases on average, but is 0% for groups one and two. Group three is characterized by death (32.14%). Since multiple diagnoses may be listed for an individual and since we combined all of an individual diagnostic information, probabilities total to more than 100% over all diagnoses. In other words, it is not unlikely that someone over 65 years old who sees a physician will see a physician for several different problems.

In any event, differences between the overall probability of the event and the probabilities for each group are used to identify the pure types. Thus, group one seems to be characterized by minor problems, is younger, often on welfare, and is the least expensive group to treat. Group two is characterized by visits for infectious disease and a wide variety of other conditions, this group incurs fairly high physician costs but is less costly in total than group three. Group three are the sickest people. Persons in this group are characterized by hospital visits for a large range of conditions, often die, and are the most expensive group to treat, although cost, like hospitalization, was not used as a grouping variable. GOM identified three basic groups--the worried well, people who have some illness, and persons who are very sick. The costs of treating these types varies in consequence of these definitions. We should also note again that the data used for this analysis were far from perfect. Cleaner data would almost certainly result in the formation of additional groups. Distinctions are blurred by the presence of errors in data.

## 4.7 FURTHER ANALYSIS--BLENDING RATES AND THE UTILITY OF INFORMATION

As indicated in our earlier discussion, we will use a strategy for determining price levels that has both discrete and continuous components. Both the discrete and continuous components are defined by the GOM analyses presented above. The "discrete" component involves the identification of logically discrete dimensions, here the three pure types, that best describe the variation of the internal variables, i.e., the individual's attributes. The continuous component is the mixing or blending of each of the logically distinct components to best describe the observed attributes of any given hospital. The blending coefficients are the $g_{ik}$'s which relate each individual to each of the three pure types.

Our goal is to create a price for each pure type and use these pure type prices to create a unique set of capitation rate prices for each individual. This approach recognizes the unique characteristics of each individual because it does not require that people be grouped into artificially "similar" categories. For example, assume that the price level for pure type one is \$1,000 and the price level for pure type two is \$500. Individual "A" is described as 50 percent pure type one and 50 percent pure type two. In this event, the capitation rate for this person would be \$1500/2 = \$750. Someone more like the expensive pure type (i.e., the $g_{ik}$ on the first pure type for this person is greater than 0.5) would receive a higher rate while someone more like pure type two would receive a lower rate.

However, at this point our problem is that most people cannot be uniquely assigned to any single type, e.g., the "pure type" is unobserved. Thus, a method to derive prices using the $g_{ik}$'s and the individual's total cost is required.

In order to understand the solution to this problem, it is useful to look at payment under a capitation system. If we let $P_K$ represent the price load of pure type K, then under this blended rate concept, the average rate (AR) will be:

3) $AR_i = (g_{i1} P_1 + g_{i2} P_2 + g_{i3} P_3 + g_{i4} P_4)$, where

$g_{ik}$ is the grade of membership (the blending coefficient) of individual i in pure type K.

Our unknowns are the $P_K$s--the prices for each pure type group. What is needed are prices that minimize the difference between the actual cost (TC) and the capitation rates revenue. Given this objective, we can use ordinary least squares to create the prices. This was done by estimating:

4) $TC_i = g_{ik} P_k + e.$

Since TC was skewed, so we also estimated:

5) $LN(TC_i) = g_{ik} P_k + e.$

This equation was estimated using three capitation scenarios:

1. HMO Model, i.e., all Part A plus all Part B
2. All Part B
3. Case Manager Model (includes only outpatient care)

These represent three levels of inclusiveness for capitation rates.

For each of these dependent variables we used the four separate sets of GOM pure type groups based on increasing amounts of information described above. These four sets were:

1. Outpatient diagnosis
2. (1) plus inpatient diagnosis
3. (2) plus death (from Medicare files)
4. (3) plus AAPCC variables

The purpose was to determine whether the additional information increased our ability to predict total charges in one of the above categories for an individual. The ability to explain variation in the dependent variable (charges) using one of the GOM sets of groups is measured by a statistic known as $r^2$. This statistic measures the explanatory power of the model.

Table 4-2 presents the $r^2$ statistics for the four regression equations for each of the three scenarios. All results clearly favored the logarithmic function, indicating that this transformation is appropriate for these data. The results reported here are, therefore, from the logarithmic versions.

TABLE 4-2
$r^2$ FOR FOUR SETS OF GOM GROUPS AGAINST THREE DEPENDENT VARIABLES, SOUTH CAROLINA DATA

DEPENDENT VARIABLE:
HMO

| Grouping variables | Adjusted $r^2$ |
|---|---|
| Outpatient Dx | 6.4% |
| + Inpatient Dx | 64.5% |
| + Death | 63.2% |
| + AAPCC | 63.6% |

DEPENDENT VARIABLE:
All Part B

| Grouping Variable | Adjusted $r^2$ |
|---|---|
| Outpatient Dx | 35.0% |
| + Inpatient Dx | 31.6% |
| + Death | 31.6% |
| + AAPCC | 31.6% |

DEPENDENT VARIABLE:
Case Manager

| Grouping Variables | Adjusted $r^2$ |
|---|---|
| Outpatient Dx | 2.7% |
| + Inpatient Dx | 3.5% |
| + Death | 3.5% |
| + AAPCC | 2.0% |

By way of contrast, the same statistic for two of the scenarios are presented in Table 4-3.

### TABLE 4-3

### MAXIMUM TOTAL EXPLAINED, VARIATION AND THE CONTRIBUTION OF SELECTED VARIABLES

| Variable | H.M.O | All Part B |
|---|---|---|
| AAPCC* (four) | 3.0% | 3.3% |
| Plus Disease | +12.2% | +22.1% |
| Plus Mortality | +1.0% | 0% |
| Plus Inter-action** | +0.8% | +1.2% |
| Maximum Total | 16.2% | 26.3% |

*Institutional Status does most of the work
**This includes all possible interactions

It is important to note that the GOM results reported in section 4.6 were obtained from a 4,000 person random sample from the 1981 South Carolina data. Since the regression estimates reported above required a separate sample from the same base data set, the blending coefficients (the $G_{ik}$'s) needed to be estimated for this new sample from the South Carolina data. In other words, we did not wish to base these results on the same people used to create the groups in the first place. This was accomplished by first estimating a linear equation using the original 4,000 person sample where the blending coefficients were the dependent variable and all of the other variables were independent variables. The $r^2$ for this equation was more than 98%. Thus, the shrinkage in generalizing from groups derived on a sample to the population is minimal. This is confirmed by comparing the $r^2$ statistic from an initial regression, like the regression used for Tables 4-2, but estimated on the original 4,000 person sample, i.e., the sample used to create the groups. The coefficients and statistics were virtually identical. We suspect, but cannot prove, that this lack of shrinkage may be a property of the GOM model. It is, in any event, a striking finding, and one which was unexpected. Generally, in moving an estimate to another population the ability to explain variance decreases.

## 4.8 DISCUSSION--THE UTILITY OF TYPES OF INFORMATION FOR GOM IN DIFFERENT CONTEXTS

### 4.8.1 The HMO Model

Table 4-2 presents the $r^2$ values for the HMO model. The HMO model is a single payment for all Part A and B services. The first set of GOM groups based only on outpatient diagnosis information "explains" only 6.4% of the variation in total cost. When inpatient diagnostic information is added, these GOM groups do much better--explaining 64.5% of the total variation. GOM appears to use these variable as an indication that someone was hospitalized. Hospitalized (Yes/No) was not a variable, but the South Carolina diagnostic information from hospitals clearly conveys this fact. Additional information results in GOM groups that do almost as well--but not better. (In truth, the mortality and AAPCC variables seem to act more like noise than information).

### 4.8.2 A Digression on Logarithmic Transformations

Note that the regression is fit to the logarithm of the observed costs. This means that using the least squares estimated $g_{ik}$ values and the cost coefficients of the pure types one can form a blended rate of the logarithm of the health care costs. To determine individual costs, average costs or total costs (not on the log scale) one must transform back to the original scale. Unfortunately this does not mean that simply exponentiating (inverting the log transform) the predicted log costs will yield the predicted costs back again. This is seen as follows.

Let y be log normally distributed with parameters $\mu$ and $r^2$. By this we mean that $Z = \log y$ has a normal distribution with mean $\mu$ and variance $r^2$. The mean of y, however, is $\exp(\mu + \frac{1}{2}r^2)$. In our case the random variable y represents the costs and the random variable Z represents the logarithm of the cost.

Suppose that a set of concomitant variables $X = (X_1 \ldots X\ )$ exists which we can use to estimate the value of $\mu$. In our case these X values would be the observed demographic and disease variables used to get the $g_{ik}$ values. For any particular individual with a vector of concomitants, $X_1$, say, the estimated log cost, $\hat{\mu}_{Z/X}$, is arrived at by putting these X values into the fitted regression equation. The residual is the actual log cost minus the estimated log cost $\mu_{Z/X}$. The sum of squares of the residuals over all observed log costs is an estimate of $r^2$ when suitably standardized by the sample size. Put in formula form, the estimate $r^2$ based on n observed log cost values is:

$$6)\quad \hat{r} = \frac{\sum^{n}(Z_i - \hat{\mu}_{Z/x_i})}{n-p}$$

To estimate the costs on the original scale for an individual with concomitant vector X, we set

$$7)\quad \hat{y} = \exp(\hat{\mu}_{Z/X} + \tfrac{1}{2}\hat{r}^2)$$

Note that, in effect, in addition to reversing the log transform by exponentiating the estimated log cost, we need to multiply by the factor $\exp(\tfrac{1}{2}\hat{r}^2)$. If we were able to group the individuals according to say similar values of X, equation (7) should result in a value close to the arithmetic mean cost of the group (on the original scale). If the back fitted mean cost (equation 7) is not approximately equal to the grouped mean, a further group adjustment is required. This group specific adjustment may be required because of a violation in the assumption that the costs are log-normally distributed. Although group to group adjustment factors may be required, due to deviations of the distribution of costs from the log-normal assumptions this will not negate the estimate of $\mu_{Z/X}$ or of the GOM values. The confidence intervals calculated on the original scale may, however, be slightly off.

It is interesting to note that under the assumption of a log normal cost distribution and a log-normal process, the year to year change in $\hat{r}^2$ is a measure of the inflation of health care costs. Given an index relating health care costs to economic factors, future health care costs can be predicted from the GOM log-normal analysis based only upon a change in the health care costs through altering $\hat{r}^2$ and a change in the demographic profile by altering the mixed $g_{ik}$ values in the population.

### 4.8.3 Comparison to Fixed Boundary Groups

Turning to Table 4-3, it can be seen that the maximum $r^2$ available from all of these data used in fixed boundary groupings is 16.2%. Thus, the discrete type group, blended rate strategy appears much more effective in using the available data for computing capitation rates for HMO's. This is a very significant finding if capitating small organizations is to become a truly viable option. However, since the inpatient diagnostic information also conveyed the fact of hospitalization, this comparison includes this variation explained by GOM; about 50% of the difference is due to this.

### 4.8.4 The Value of Information for GOM

The GOM results, do however, strongly imply that complete diagnostic information (outpatient plus inpatient) is important, but that neither mortality or AAPCC type variables matter very much in the HMO context. This is confirmed by ANOVA results shown in Tables 4-3. The AAPCC variables even when considered first, explain only 3.3% of the total variation. Again, disease (diagnosis) is most important, accounting for 22.1% of the total possible 26.3% variance reduction. Contrary to conventional wisdom, mortality is not very important. Finally, all possible interactions of all of these variables adds only 1.2% to the variance reduction.

Another variable of potential interest is prior utilization. However, several years data were not available for this project. Thus, a comparison of the use of prior utilization to predict current utilization with the above results must be based on results obtained elsewhere. This comparison is of concurrent versus predictive adjustment. GOM would certainly do less well as a predictor than it does when used concurrently. Beebe, Lubitz and Eggers (1985) used data from the Medicare statistical system to construct a formula in order to test prior utilization for adjusting capitation rates. They used 1974, 1975 and 1976 data to construct the equation and 1977, 1978, and 1979 data to evaluate the model. They report the $r^2$ statistics for the equation development process but not for the evaluation. The $r^2$'s for their prior utilization equations were always less than 5 percent. These equations also included demographic (AAPCC) information. Their equations are different from those reported above in that they predict 1976 using 1974 and 1975 data.

In a similar vein, Ash (1985) divides the Medicare population into three categories using 1979 data: those with no expenses, those with some expenses but no hospital expenses, and those with hospital expenses. Using regression equations (which include various measures of prior utilization) within each of these group and summing the explained variation in 1980 costs across the three groups results in a maximum $r^2$ of slightly better than 10%. For comparison, using AAPCC variables as predictors results in less than one percent explained variance (0.9%). Note that both attempts at explaining one year's cost using a prior year's utilization provided only a small reduction in variance. In addition, predicting costs using AAPCC variables reduces their effectiveness from the concurrent 3.3% to 0.9%. We turn to the utility of these variables in the All B scenario next.

### 4.8.5 The All Part B Scenario

The All Part B scenario assumes that a physician is responsible for paying for all physician (in and outpatient) costs and for all outpatient services (laboratory tests, procedures etc.). The set of GOM groups that performed best in terms of variation explained for this scenario was the first set--the set formed using only outpatient diagnostic information. Additional information was of no value in improving the $r^2$. Although the variance explained here by GOM (35%) is not as large as the variance explained by the second set of GOM groups for the HMO model (64.5%), the total variation to be explained is less since the variation due to hospital charges does not appear in the All B scenario. The second GOM set uses hospital diagnostic information which the first set does not. Hospital information is of value in explaining variation in hospital charges.

### 4.8.6 The Case Manager Scenario

The next scenario tested against the GOM model is the case manager scenario--capitation for outpatient care. In this case the model explained 3.6% of the variation, at best. The distinction between out and inpatient diagnostic information mattered, but the increase in variance explained (2.7% - 3.5% = 1.2%) is so small that its significance is open to question. We have no basis against which to compare this result. Thus, we can note only that the variance explained is very small, and that this variance must be related to variables not present in our data set. The amount of variance explained could be improved by including (as variables) measures such as counts of outpatient visits. Since we are interested in capitation, not per visit payment, this did not appear worthwhile. It should also be noted that if only outpatient care is capitated, then inpatient care acts as a "safety valve." In other words, a very sick person will be admitted to the hospital. At this point the physician's financial liability for patient care ends. Thus, this scenario is inherently less risky than the more inclusive HMO and All B scenarios. Since variation cannot be explained using patient related variables, capitation for outpatient care might better be approached through grouping physicians.

In evaluating the use of various risk factors in adjusting capitation rates, several important factors need to be remembered. For example, the basic design of a system effects the total risk shifted to providers. Capitating a large geographic area (area capitation) and the HMO scenario inherently shift the most risk to providers. The All B scenario shifts less risk because hospital care and long term care are potential safety valves. A very sick enrollee can be admitted to an institution and the provider, under this scenario, is liable only for physician costs while the patient is in the hospital. The Case manager scenario--capitation for outpatient care--eliminates even this expense, further reducing the provider's risk.

## 4.9 SUMMARY AND CONCLUSIONS

The purpose of this chapter was to explore the use of the Grade of Membership (GOM) model in adjusting capitation rates under three capitation scenarios. In addition, the utility of various kinds of information for GOM was assessed. The first step in this process was to define the Grade of Membership model.

Following that description, GOM was used to find "pure type" groups in the Medicare population. Three groups were found. The first group was younger, characterized by minor problems, often on welfare, and the least expensive to treat. The second group incurred fairly high physician costs for a wide variety of infections and other conditions. Group three was the most expensive. Persons in this group were the most likely to die and/or to be hospitalized--again for a variety of conditions. Of course these groups were defined on an imperfect and somewhat restrictive data set. More accurate and more complete data would result in additional groups.

These pure type groups were assigned a price using ordinary least squares regression. From these prices, a blended rate for each individual was computed. These prices and rates were computed for three capitation scenarios: Part A plus B, Part B, and Part B outpatient only. This analysis for each scenario was repeated three times using sets of four GOM groups based on increasing amounts of information. The utility of the additional information was evaluated in terms of additional explained variance in the regression estimates. In this analysis, we found:

- Pure types can be moved from a sample to a population with virtually no shrinkage i.e., with less than two percent loss of explained variance.

- For Parts A & B, GOM was able to explain about 64 percent of the variation in charges. This compares to about 4 percent for the AAPCC and about 5-10 percent for approaches that use prior utilization to predict an individuals resource use. This comparison, however, includes the fact that GOM had information that someone was or was not hospitalized, as conveyed by the inpatient diagnostic data. In a sense, then, this is a model of a combined capitation/DRG payment system. In addition, GOM was always used as a concurrent adjustment. This is necessarily more powerful than a prediction, especially when hospitalization is known.

From a providers point of view sixty-four percent reduction in explained variation is equivalent to increasing reserves against loss by sixty-nine percent. Fore reference, a ten percent reduction in variance translates to a 5.4 percent increase in effective provider resources, and 4 percent explained variance is equivalent to increasing provider resources by about 2 percent.

The most important information for GOM for Parts A & B was the combination of inpatient and outpatient diagnosis. AAPCC variables and mortality did not add to explained variance. This is because GOM is a pattern recognition technique. Analysis of variance would produce different results--mortality and institutional status would be as important as diagnosis.

- For Part B, outpatient diagnosis was important. The remaining information was not useful in increasing explained variation. Explained variation for Part B was 35 percent. Again, this is much higher than the variation that can be explained using more conventional techniques.

- For outpatient care, GOM was able to explain only about 3.5 percent of the variation in per user charges. In part, this is because the total variation of these charges is much less than the variation in the other broader charge categories. The unexplained variation must be related to variables not used in this analysis. Type of physician practice might be useful in this context.

- The prices for the GOM groups were derived from a logarithmic cost function. The appropriateness of the inflated anti-logarithms of these values as price was demonstrated.

In conclusion, we believe that the analyses described above indicate that GOM is potentially useful for adjusting prices for capitation payment. While we would not argue that all of the variables we used or the way these variables were transformed is the only way to approach this problem, it seems clear that if capitating small organizations (e.g., HMOs) is a desirable policy option, then the GOM strategy is worthy of serious additional research.

## TABLE 4-1

## GOM PURE TYPE GROUPS, SOUTH CAROLINA DATA, PARTS A AND B

| VARIABLE | ALL | GP 1 | GP 2 | GP 3 |
|---|---|---|---|---|
| 1. Infectious Parasite | | | | |
| Yes | 0.0480 | 0.0397 | 0.1414 | 0.0000 |
| No | 0.9520 | 0.9603 | 0.8586 | 1.0000 |
| 2. Cancer | | | | |
| Yes | 0.1052 | 0.0976 | 0.1934 | 0.0606 |
| No | 0.8947 | 0.9024 | 0.8066 | 0.9394 |
| 3. Diabetes | | | | |
| Yes | 0.1185 | 0.1094 | 0.2253 | 0.0630 |
| No | 0.8815 | 0.8906 | 0.7747 | 0.9370 |
| 4. Mental/Drug | | | | |
| Yes | 0.0692 | 0.0000 | 0.4014 | 0.0000 |
| No | 0.9307 | 1.0000 | 0.5986 | 1.0000 |
| 5. Eye | | | | |
| Yes | 0.1475 | 0.1749 | 0.0713 | 0.1356 |
| No | 0.8525 | 0.8251 | 0.9287 | 0.8644 |
| 6. Heart | | | | |
| Yes | 0.3590 | 0.0000 | 1.0000 | 0.0000 |
| No | 0.6410 | 1.0000 | 0.0000 | 1.0000 |
| 7. Hypertension | | | | |
| Yes | 0.1900 | 0.1661 | 0.3957 | 0.1007 |
| No | 0.8100 | 0.8339 | 0.6043 | 0.8993 |

|  |  |  |  |  |  |
|---|---|---|---|---|---|
| 8. | Stroke |  |  |  |  |
|  | Yes | 0.0502 | 0.0245 | 0.1623 | 0.0352 |
|  | No | 0.9497 | 0.9755 | 0.8377 | 0.9648 |
| 9. | Circulatory |  |  |  |  |
|  | Yes | 0.0892 | 0.0489 | 0.3552 | 0.0000 |
|  | No | 0.9107 | 0.9511 | 0.6448 | 1.0000 |
| 10. | Pneumonia |  |  |  |  |
|  | Yes | 0.0313 | 0.0000 | 0.1841 | 0.0000 |
|  | No | 0.9688 | 1.0000 | 0.8159 | 0.1000 |
| 11. | Lung |  |  |  |  |
|  | Yes | 0.1087 | 0.0000 | 0.6479 | 0.0000 |
|  | No | 0.8912 | 1.0000 | 0.3521 | 1.0000 |
| 12. | Ulcers |  |  |  |  |
|  | Yes | 0.0692 | 0.0000 | 0.4613 | 0.0000 |
|  | No | 0.9307 | 1.0000 | 0.5387 | 1.0000 |
| 13. | Abdominal |  |  |  |  |
|  | Yes | 0.0767 | 0.0000 | 0.4959 | 0.0000 |
|  | No | 0.9232 | 1.0000 | 0.5041 | 1.0000 |
| 14. | Cirrhosis |  |  |  |  |
|  | Yes | 0.0290 | 0.0000 | 0.1808 | 0.0000 |
|  | No | 0.9710 | 1.0000 | 0.8192 | 1.0000 |
| 15. | Renal |  |  |  |  |
|  | Yes | 0.1272 | 0.0881 | 0.4708 | 0.0000 |
|  | No | 0.8727 | 0.9119 | 0.5292 | 1.0000 |
| 16. | Skin |  |  |  |  |
|  | Yes | 0.0882 | 0.0721 | 0.2033 | 0.0462 |
|  | No | 0.9117 | 0.9279 | 0.7967 | 0.9538 |

|  |  |  |  |  |
|---|---|---|---|---|
| 17. Arthritis |  |  |  |  |
| Yes | 0.1292 | 0.0000 | 0.6706 | 0.0000 |
| No | 0.8707 | 1.0000 | 0.3294 | 1.0000 |
| 18. Joint.P |  |  |  |  |
| Yes | 0.0945 | 0.0000 | 0.5444 | 0.0000 |
| No | 0.9055 | 1.0000 | 0.4556 | 1.0000 |
| 19. Symptoms |  |  |  |  |
| Yes | 0.1482 | 0.0000 | 1.0000 | 0.0000 |
| No | 0.8517 | 1.0000 | 0.0000 | 1.0000 |
| 20. Fracture |  |  |  |  |
| Yes | 0.0552 | 0.0000 | 0.3202 | 0.0000 |
| No | 0.9447 | 1.0000 | 0.6798 | 1.0000 |
| 21. Other B |  |  |  |  |
| Yes | 0.2912 | 0.0000 | 1.0000 | 0.0000 |
| No | 0.7087 | 1.0000 | 0.0000 | 1.0000 |
| 22. Other A |  |  |  |  |
| Yes | 0.0172 | 0.0000 | 0.0000 | 0.0753 |
| No | 0.9827 | 1.0000 | 1.0000 | 0.9247 |
| 23. Infectious/Parasitic |  |  |  |  |
| Yes | 0.0027 | 0.0000 | 0.0000 | 0.0121 |
| No | 0.9972 | 1.0000 | 1.0000 | 0.9879 |
| 24. Cancer |  |  |  |  |
| Yes | 0.0142 | 0.0627 | 0.0000 | 0.0000 |
| No | 0.9857 | 1.0000 | 1.0000 | 0.9373 |
| 25. Diabetes |  |  |  |  |
| Yes | 0.0075 | 0.0000 | 0.0000 | 0.0328 |
| No | 0.9925 | 1.0000 | 1.0000 | 0.9672 |

| | | | | | |
|---|---|---|---|---|---|
| 26. | Metabolic | | | | |
| | Yes | 0.0075 | 0.0000 | 0.0000 | 0.0252 |
| | No | 0.9942 | 1.0000 | 1.0000 | 0.9748 |
| 27. | Blood | | | | |
| | Yes | 0.0045 | 0.0000 | 0.0000 | 0.0197 |
| | No | 0.9955 | 1.0000 | 1.0000 | 0.9803 |
| 28. | Mental/Drug | | | | |
| | Yes | 0.0085 | 0.0000 | 0.0000 | 0.0372 |
| | No | 0.9915 | 1.0000 | 1.0000 | 0.9628 |
| 29. | Nerve/Eye | | | | |
| | Yes | 0.0072 | 0.0000 | 0.0000 | 0.0317 |
| | No | 0.9927 | 1.0000 | 1.0000 | 0.9683 |
| 30. | Heart.D | | | | |
| | Yes | 0.0492 | 0.0000 | 0.0000 | 0.2159 |
| | No | 0.9507 | 1.0000 | 1.0000 | 0.7841 |
| 31. | Stroke | | | | |
| | Yes | 0.0125 | 0.0000 | 0.0000 | 0.0547 |
| | No | 0.9875 | 1.0000 | 1.0000 | 0.9453 |
| 32. | Atherosclerosis | | | | |
| | Yes | 0.0060 | 0.0000 | 0.0000 | 0.0263 |
| | No | 0.9940 | 1.0000 | 1.0000 | 0.9737 |
| 33. | Respiratory | | | | |
| | Yes | 0.0025 | 0.0000 | 0.0000 | 0.0110 |
| | No | 0.9975 | 1.0000 | 1.0000 | 0.9890 |
| 34. | Pneumonia | | | | |
| | Yes | 0.0045 | 0.0000 | 0.0000 | 0.0197 |
| | No | 0.9955 | 1.0000 | 1.0000 | 0.9803 |

|  |  |  |  |  |  |
|---|---|---|---|---|---|
| 35. | Other Lung |  |  |  |  |
|  | Yes | 0.0112 | 0.0000 | 0.0000 | 0.0494 |
|  | No | 0.9887 | 1.0000 | 1.0000 | 0.9506 |
| 36. | Digestive |  |  |  |  |
|  | Yes | 0.0052 | 0.0000 | 0.0000 | 0.0230 |
|  | No | 0.9947 | 1.0000 | 1.0000 | 0.9770 |
| 37. | Hernia |  |  |  |  |
|  | Yes | 0.0042 | 0.0000 | 0.0000 | 0.0186 |
|  | No | 0.9957 | 1.0000 | 1.0000 | 0.9814 |
| 38. | Enteritis |  |  |  |  |
|  | Yes | 0.0087 | 0.0000 | 0.0000 | 0.0384 |
|  | No | 0.9912 | 1.0000 | 1.0000 | 0.9616 |
| 39. | Liver |  |  |  |  |
|  | Yes | 0.0050 | 0.0000 | 0.0000 | 0.0218 |
|  | No | 0.9950 | 1.0000 | 1.0000 | 0.9782 |
| 40. | Lemitourinary |  |  |  |  |
|  | Yes | 0.0102 | 0.0000 | 0.0000 | 0.0448 |
|  | No | 0.9897 | 1.0000 | 1.0000 | 0.9552 |
| 41. | Reproductive |  |  |  |  |
|  | Yes | 0.0080 | 0.0000 | 0.0000 | 0.0350 |
|  | No | 0.9920 | 1.0000 | 1.0000 | 0.9650 |
| 42. | Skin |  |  |  |  |
|  | Yes | 0.0060 | 0.0000 | 0.0000 | 0.0263 |
|  | No | 0.9940 | 1.0000 | 1.0000 | 0.9737 |
| 43. | Musculoskeletal |  |  |  |  |
|  | Yes | 0.0025 | 0.0000 | 0.0000 | 0.0110 |
|  | No | 0.9975 | 1.0000 | 1.0000 | 0.9890 |

| | | | | | |
|---|---|---|---|---|---|
| 44. | Symptoms | | | | |
| | Yes | 0.0150 | 0.0000 | 0.0000 | 0.0657 |
| | No | 0.9850 | 1.0000 | 1.0000 | 0.9343 |
| 45. | Fracture | | | | |
| | Yes | 0.0050 | 0.0000 | 0.0000 | 0.0219 |
| | No | 0.9950 | 1.0000 | 1.0000 | 0.9781 |
| 46. | Hip.Frac | | | | |
| | Yes | 0.0040 | 0.0000 | 0.0000 | 0.0175 |
| | No | 0.9960 | 1.0000 | 1.0000 | 0.9825 |
| 47. | Injury | | | | |
| | Yes | 0.0072 | 0.0000 | 0.0000 | 0.0318 |
| | No | 0.9927 | 1.0000 | 1.0000 | 0.9682 |
| 48. | Bad A Dx | | | | |
| | Yes | 0.1487 | 0.5017 | 0.0000 | 0.0000 |
| | No | 0.1477 | 0.4983 | 0.0000 | 0.0000 |
| | No Dx's | 0.7035 | 0.0000 | 1.0000 | 0.0000 |
| 49. | Bad B Dx | | | | |
| | Yes | 0.0075 | 0.0000 | 0.0000 | 0.0328 |
| | No | 0.0097 | 0.0000 | 0.0000 | 0.0427 |
| | No Dx's | 0.9827 | 1.0000 | 1.0000 | 0.9245 |
| (set 3) | | | | | |
| 50. | Death | | | | |
| | Yes | 0.0765 | 0.0000 | 0.0000 | 0.3214 |
| | No | 0.9235 | 1.0000 | 1.0000 | 0.6786 |
| (set 4) | | | | | |
| 51. | Welfare | | | | |
| | Yes | 0.2110 | 0.2815 | 0.2212 | 0.0000 |
| | No | 0.7890 | 0.7185 | 0.7788 | 1.0000 |

| | | | | |
|---|---|---|---|---|
| 52. Sex | | | | |
| Male | 0.3452 | 0.3215 | 0.2895 | 0.4511 |
| Female | 0.6547 | 0.6785 | 0.7105 | 0.5489 |
| 53. Age | | | | |
| 65-69 | 0.2825 | 0.3191 | 0.1504 | 0.2875 |
| 70-79 | 0.4967 | 0.4692 | 0.6982 | 0.4154 |
| 80+ | 0.2207 | 0.2117 | 0.1514 | 0.2971 |
| Total Cost | | | | |
| To < 30 | 0.0940 | 0.1661 | 0.0000 | 0.0000 |
| To < 80 | 0.1590 | 0.2809 | 0.0000 | 0.0000 |
| To < 340 | 0.2540 | 0.4483 | 0.0000 | 0.0011 |
| To < 2090 | 0.2452 | 0.1027 | 0.7469 | 0.2137 |
| 2090 + | 0.2477 | 0.0019 | 0.2531 | 0.7852 |

# CHAPTER FIVE
# RISK AS RELATED TO THE SIZE OF THE ENROLLED POPULATION FOR HEALTH MAINTENANCE ORGANIZATIONS

## 5.1 INTRODUCTION

One of the traditional interests of economists is in the economies or diseconomies of large scale operation. In the health care field an organizational type of particular interest to policy makers at the State and Federal levels is the health maintenance organization (HMO). HMOs are paid a fixed fee to provide all health care services for an individual for a fixed time period, usually one year. Given this payment mechanism, HMOs have a financial incentive to keep their enrollees healthy and to provide any medical services needed by an enrollee at minimum cost. These global incentives for economy are the reason for the policy interest in HMOs.

An HMO combines the functions of a health provider and a health insurer. Thus, in considering economies of scale for HMOs, two areas of research are possible. First, one could consider economies of scale in health care delivery. For example, larger organizations might more easily substitute lower paid labor for higher paid labor, e.g., physician's assistants for physicians; obtain capital more cheaply; and enroll people more effectively. Alternatively, one might investigate economies of scale for HMOs in performing their insurance function. The purpose of this paper is to present an analysis of economies of scale in a critical aspect of insurance--bearing risk. Specifically we evaluate the relationship between the number of persons enrolled in a HMO and the HMO's risk of financial ruin.

This is obviously an important issue for the HMO. The issue is also important for Federal and State policy makers because HMOs are often put forward as an important part of the solution to the rising costs of health care. If a particular size is preferred in terms of provider risk, then organizations of this size might be encouraged. Alternatively, if certain common sizes are found to represent inherently high risks of financial ruin, then measures to limit or control risk for these organizations would become increasingly important.

In assessing the risk for commercial insurers, the larger the number of policy holders the better as far as risk is concerned. This is because a larger enrolled group reduces the impact of random fluctuations in necessary health care expenses on the solvency of the organization. However, for HMOs, the same concept will not hold true if:

1. The HMO does not look at perpetual solvency but solvency for finite time.

2. The HMO's reserve account is not required to remain always positive but rather the reserves must be balanced only at certain points in time such as the end of the fiscal year.

It is also important that, as a practical matter, for HMOs, "large" means an enrollment of 50,000 or 100,000 persons. For commercial insurers, this is small.

When these conditions hold, the optimal size of an HMO is not necessarily the maximum number possible. In the following sections we use the results of risk theory to determine the optimal enrollment size for an HMO. Our results are based on certain distributed statistics obtained from 1981 Medicare claims data--a five percent sample of Medicare beneficiaries. Our specific conclusions are most applicable to an HMO enrolling only this population; however, these results are easily generalized to the general population or any specific subset.

## 5.2 ASSUMPTIONS AND DEFINITIONS

In order to evaluate the relationship between risk and enrollment size the following eight assumptions and definitions are required:

1. The HMO is not ruined if its reserve account, i.e., capitation payments plus risk reserve minus costs for health care provided, is non-negative at the end of the fiscal year.

2. Each of the "(N)" enrollees has a probability (p) of needing health care services during the year. As noted above, the model presented here can be easily extended any risk factor group, each having its own probability of needing medical services.

3. Each enrollees health care requirements is independent of all other enrollees' health care requirements.

4. Given that an enrollee receives health care during the year; the average annual Medicare charge is denoted $\mu$ and the variance of the annual charge is denoted $r^2$. Both of these values are known.

5. The per capita payment is equal to the expected health care charge plus a small fraction (e.g., 0.01) of the expected charge for risk loading. This loading proportion is denoted E.

6. The actual average cost for the year is approximately a normally distributed random variable.

7. The total amount the health care provider can lose at the end of the year in addition to the risk loading and still be solvent is denoted R. R is the reserve level for the HMO.

8. The risk level $\varepsilon$ is the probability that the health provider will become insolvent at the end of the year.

Under the above assumptions the unconditional cost per capita for health care is given by:

$$M = p \cdot \mu \tag{1}$$

The variance of this cost, per capita is:

$$V = p\ (1 - p)\ \mu^2 + pr^2 \tag{2}$$

By assumption, the per capita reimbursement is M (1 + E). Therefore, for an HMO that enrolls N individuals, the total paid at the end of the year is N · M (1 + E). The total cost for health care is a random variable with mean NM and variance NV. To determine the probability of insolvency at the end of the year we use the properties of normal distribution and the additional amount R that the provider can lose. In this case, the probability of insolvency is:

3) $$P\left(z > \frac{R + NME}{\sqrt{NV}}\right)$$

Where Z is the standard normal random variable.

To illustrate the relationship of the size of the enrolled cohort (N) and the probability of insolvency during a year it is useful to consider the likelihood of ruin at any time over 25 years. The health provider is considered ruined if at the end of any year the costs of health care for that year exceeds the value NM(1+E)+R. Note that we are assuming that the HMO does not augment its reserves from year to year by, say, caring forward a surplus. In order to evaluate risk, it is necessary to use estimates for the values of the variables in these expressions. Using total part B charges for a 5% sample of the Medicare population we estimate $\mu$=\$771 and $r^2 = 1.5523 \times 10^6$. From Gresch and Leong (1983) we will assume p = .565. Using these estimates the probability of ruin of the health provider in 25 years given E=0.01 and R=\$100,000 can be calculated. The plot of this ruin probability as a function of N is given in Figure 1. Naturally the shape of this curve depends on E. Figures 2A and 2B give two different views of a 3-D plot of ruin probability as a function of both enrollment size and of risk loading, E. From these three figures we see that for risk reserve of R=$100,000 an enrollment of between 10,000 and 30,000 individuals is the worst situation. For sizes less the $10,000 the reserves, i.e., the value of R=$100,000, dominates any adverse fluctuation in costs. For large N, say greater than 100,000, the law of large numbers dominates the random fluctuations. This figure implies that there isn't a best size but instead there is a worst enrollment size, i.e., between 10,0000 and 30,000.

However, some might argue that it is unreasonable to assume that a health provider with only 5,000 enrollees will have the same risk reserve (R) as a health provider with say 100,000 enrollees. Therefore, the above analysis will be modified to allow reserves to vary with size of enrollment. Simply assuming that the risk reserve for a health provider is proportional to the number of enrollees results in the conclusion that the larger the enrollment the better. However this assumption is unrealistic because this level of reserve is excessive for large health providers. For example if a provider with 5,000 enrollees had a reserve of $100,000 then one with 100,000 enrollees would have a reserve of $2 million. Assuming that reserves are related to some root (e.g., square root) of enrollment size is more in keeping with industry practices. Figures 3A and 3B are two different views of the plot of the ruin probability where reserves are assumed to a function of N and a proportionality constant r, i.e., $R = r \cdot \sqrt{N}$

Figures 4A and 4B give a similar plot for $\sqrt[3]{N}$ and R. Note that in Figures 4A and 4B we again see a worst enrollment size appearing in the middle range of the plot. Thus, the initial result of a worst enrollment size holds when the initial assumption of a fixed reserve level is relaxed and made realistic.

## 5.3 EVALUATING THE SIZE OF ENROLLMENT

The above results indicated that the optimal enrollment size is a function of the risk level $_£$, the risk reserve R and the risk loading E. In this section we examine the probability of ruin in a single year. Our purpose is to more precisely understand the results described above. If the risk level is set at $_£$, from expression (1) above £ is:

$$4) \qquad £ = \text{Prob} \left\{ z > \frac{R + NME}{NV} \right\}$$

This allows derivation of the following equation relating risk reserve to enrollment size.

5) $$£ = z_{1-2} \sqrt{N} \sqrt{V} - NME,$$

Where $z_{1-2}$ is that z score such that the probability of a standard normal random variable being less than or equal to $z_{1-2}$ is 1-2.

Table 1 gives the value of R for various values of N given $\mu = 771$, $r^2 = 1.55 \times 10^6$ $p = .565$ and $E = .01$ and $E = 0.2$. With probability £ the health provider will need no more than the appropriate risk reserve entry. Negative values mean that at least this amount of surplus will be generated with probability 1-2.

We see from Table 1, depending on E and £ some enrollment sizes are much worse than others. For example, with £ = .01 and E = .01 the risk reserve is $191,599 for an enrollment of 10,000 and $308,023 for 50,000 enrollees. This is an increase of over 50% in the required reserve. However, the required reserve for 100,000 enrollees is this case is almost identical to that required for 50,000 enrollees. With an enrollment of 500,000 this analysis indicates a 99% change of having a surplus at the end of the year of at least $515,258. From Table 1 one would guess that for E = .01 and £ = .01, the worst enrollment size is somewhere between 50,000 and 100,000 individuals. The worst case here is defined as the enrollment size that has the largest reserve requirement.

In general, the worst enrollment size as measured by the largest required risk reserve to obtain a fixed risk value £ can be determined by differentiating equation (5) and equating to zero. Explicitly, the worst enrollment size is given as:

$$N_W = \frac{V}{4M^2} \cdot \frac{Z^2_{1-2}}{E^2}$$

For setting $E = .01$, $V = (1011)^2$ and $M = 436$, corresponding to $\mu = 771$, $r^2 = 1.55 \times 10^6$ and $p = .565$ we get

$$N_W = 72{,}726 \text{ enrollees}$$

as the worst size. To generalize if the risk reserve is proportional to any power ( < ½) of the enrollment size, i.e., if $R = r \cdot N^B$, where $0 \leq B < ½$, then a worst size is exists and given by

$$7) \qquad N_W = \left( \frac{½ - \beta}{1 - \beta} \right)^2 \frac{V}{M^2} \cdot \frac{Z^2 \pounds - 1}{E^2}$$

Alternatively, if $B \geq ½$, then the larger the enrollment size the less the required reserve. This is a less realistic assumption than that embodied in equation seven.

Equation (7) presents an interesting rule of operation for HMOs. Explicitly the worst size can be made smaller by either increasing E, the risk loading, or increasing B thereby implicitly increasing the required risk reserve for larger health providers. Both of these assume rules that the reimbursement rates will be set with a specific value of £ in mind. It is also noteworthy that the above results depend on the variability of costs of care as expressed through the ratio of the variance to the square of the mean. Hence entering a stoploss contract will effectively change the worst size only if such a contract changes the ratio of variance to the square of the mean. This is possible under some stoploss arrangements.

The most important conclusion from this research is that instead of an optimal enrollment size, the problem for the HMO is to avoid the worst size. Suppose, however, that for some fixed £, the HMO would wish to choose N such that no reserve is required other than the risk loading accumulated during the year. Solving equation (3) for R = 0 gives the general formula for zero reserve size:

8) $$N_o = \frac{V}{M^2} \quad \frac{Z_{\pounds}^2 - 1}{E^2}$$

Note the similarity between this formula and that for the worst size, given positive reserves. From equation (6) we see that the worst size under its assumptions is one fourth the zero reserve size.

## 5.4 CONCLUSION

Our purpose was to explore the issue of the optimal size for HMOs, considering only the risk bearing functions of these organizations. Based on what we believe to be the most realistic set of assumptions regarding the relationships of reserves to enrollment size, we find that, in terms of ability to bear risk, there is a worst size for an HMO. This size is roughly 100,000 enrollees. Both smaller and larger HMOs are more able to bear the risk of financial failure.

There are several reasons that, as a matter of public policy, HMOs might be encouraged. These include increasing pure competition in the health care sector and fostering many small organizations which might be more likely to generate innovative approaches to combine quality and efficiency in health care delivery. The findings reported in this chapter imply that somehow limiting or controlling risk is very important in order to present these organizations with levels of risk that they can comfortably handle.

## TABLE 5-1

*VALUES OF R FOR CERTAIN RISK LEVELS, £, SAMPLE SIZE N AND RISK LOAD E*

---

|  | Risk £ |  |  |  |  |  |
|---|---|---|---|---|---|---|
|  | .025 (Z=1.96) | .01 (Z=2.326) | .005 (Z=2.576) | .001 (Z=3.08) | .0005 (Z=3.31) | .0001 (Z=3.65) |
| E=.01 |  |  |  |  |  |  |
| N = 1,000 | 58306 | 70008 | 78000 | 93730 | 101467 | 112337 |
| 10,000 | 154596 | 191599 | 216874 | 267828 | 291081 | 325455 |
| 20,000 | 193112 | 245441 | 281186 | 353246 | 386131 | 434743 |
| 50,000 | 225282 | 308023 | 364539 | 478477 | 530472 | 607335 |
| 100,000 | 191009 | 308022 | 387948 | 549080 | 622613 | 731313 |
| 500,000 | -776906 | -515258 | -336536 | 23766 | 188189 | 431250 |
| E=.02 |  |  |  |  |  |  |
| N = 1,000 | 53950 | 65652 | 73644 | 89374 | 97111 | 107981 |
| 10,000 | 110944 | 147947 | 173222 | 224176 | 247429 | 281803 |
| 20,000 | 105989 | 158318 | 194063 | 266123 | 299008 | 347620 |
| 50,000 | 7474 | 90215 | 146731 | 260669 | 312664 | 389527 |
| 100,000 | -244606 | -127593 | -47667 | 113465 | 186998 | 295698 |
| 500,000 | -2954986 | -2693338 | -2514616 | -2154314 | -1989891 | -1746830 |

# CHAPTER SIX
# THREE PAYMENT STRATEGIES FOR CAPITATION FOR MEDICARE

## 6.1 INTRODUCTION

The purpose of this chapter is to evaluate three basic capitation payment strategies in terms of the risk transferred to providers by each strategy. The strategies examined are potential future approaches to payment in that all three involve shifting risk from insurer to provider. Perhaps the best example, at present, of this kind of risk shifting is Medicare's PPS. However, this is not presently a widespread practice in the industry.

Capitation payment is, however, receiving greater attention as a long run alternative payment system for Medicare. This approach to paying for health care costs is one of a family of incentive-based payment systems. These incentive payment approaches work by bundling health care services into large units, in this case one person-year, and paying a pre-determined fixed rate for the bundle.

This places the provider at risk because the payment amount will be the same irrespective of the resources actually needed to treat that person for one year. This risk creates incentives for the individual or organization which receives the capitation rates to control the use of services and thereby earn a profit. One important dimension of capitation involves selection of the entity that receives the payment and its relationship to those who directly provide services. Distinctions along this dimension are used to distinguish the three strategies that will be evaluated in this chapter.

## 6.2 BACKGROUND

There are a large number of permutations and combinations of capitation payment alternatives. The basic strategies for capitation payment may be characterized along one dimension by three basic options. The first, called area capitation, involves paying an insurer a capitation rate to provide health care for all of the Medicare beneficiaries in a given geographic area. For example, a Medicare carrier or intermediary might be paid a fixed rate per person to provide care for all of the residents of a state. Blue Cross/Blue Shield of Maryland currently has submitted such a proposal to HCFA for Maryland. Alternatively, the area might be smaller. Pennsylvania Medicaid is currently completing arrangements with an insurer to capitate the insurer to provide care for all of its beneficiaries in South Philadelphia, for example. Under these circumstances, the insurer generally attempts to control the beneficiaries use of particularly high cost providers, e.g., through closed panels or high co-payments. In addition, these plans should be expected to use strict utilization control techniques.

The second strategy, called the gatekeeper strategy, also involves area-wide capitation. This strategy, however, differs from area capitation in that the gatekeeper also fills a triage role. That is, the gatekeeper sends the beneficiary who requires services to specific providers depending on the nature of the beneficiaries' problem. Thus, cancer cases would be sent to oncologists, while heart cases would be sent to cardiac specialists. This option, then, represents an expanded role for the insurer. For this option, the insurer is not a direct provider of health care.

Direct providers of care are capitated under the third option. Provider capitation blends the insurer/provider roles in one organization. In the following analysis, the number of providers in an area is treated as a variable. For this strategy, few providers with many enrollees may be thought of as equivalent to an HMO. More providers with fewer enrollees are like capitated group practices; while still more providers with still fewer enrollees are individual physician practices. Thus, important variations within this option are captured by allowing the number of providers for a fixed beneficiary population to vary.

These strategies are presented schematically in figure 6-1.

## 6.3 OVERVIEW OF THE ANALYSIS

The risk inherent in each strategy was assessed through three mathematical models--one for each strategy. In essence, the models are used to derive an expression for the variation in necessary treatment costs that a provider will probably face and the amount paid to the provider in exchange for bearing the risk associated with the variation. Each strategy was designed to spend the same total dollar amount and to produce equivalent total reserves against loss considered across all providers. Enrollment for all strategies is held constant at 100,000 persons per year.

It is very important to note that under strategies I and II, it is assumed that the insurer or gatekeeper paid providers on a risk basis similar to DRGs. That is, a provider is paid the average cost of patients in one of five disease classes based on the patients diagnosis, but only for patients who received care. This means that some risk is shifted to providers under each of these strategies. It is also assumed that the insurer or gatekeeper kept enough of the risk loading--the payment to someone for accepting a given level of risk--to insure that it did not become financially ruined. The capitation amount paid by the insurer or gatekeeper to providers is net of this amount for providers under these strategies. These providers receive the residual of the payment for accepting risk since the total dollar amount of the payment for risk is constant across the three models. Of course under provider capitation, the provider bears all of the risk and receives all of the risk load. These assumptions drive the results reported below. If the insurer does not pay providers on a risk basis (as is current practice) then the insurer bears the entire risk. This situation is covered in Chapter two, above.

Before presenting the models it is necessary to define the following notation:

$J$ = the number of specialty types. In our illustrations $J$ will be 5. The 5 specialties are related to the 5 general disease types: Cancer, diabetes, CVD, other, and no diagnosis. These are the same disease classifications which were used in other sections.

$M$ = the number of health providers for a fixed population of interests under scenario I.

$N$ = size of fixed population

$K_j$= the number of health providers specializing in care for elderly patients needing specialty care $j$ under scenario II.

$L$ = the number of capitated health providers under scenario III.

$\epsilon$ = the risk loading percentage that Medicare will pay in addition to average cost for health care.

$p$ = proportion of the population who need Medicare reimbursable health care in the year.

$p_j$= proportion of population needing Medicare reimbursable health care who have disease j. Note this is conditional upon actually needing health care and hence is a conditional probability.

$\mu_j$= average annual Medicare cost for an individual needing care with disease class j.

$\delta_j^2$= variance of annual Medicare cost for an individual with disease class j needing care.

$\mu$ = overall average annual Medicare cost for all individuals receiving Medicare reimbursable health care.

$$= \sum_{j=1}^{J} p_j \mu_j$$

$\delta^2$= variance in annual Medicare costs over all individuals receiving Medicare reimbursable health care.

$$= \sum_{j=1}^{J} p_j(\sigma_j^2 + \mu_j^2) - \mu^2$$

$r_{ij}$= the proportion of the population of N that the $i^{th}$ health provider under scenario I will see.

$w_i$= proportion of population N who seek health care who see health provider i under scenario III.

$\varepsilon^*$= risk load percentage for health providers under scenario I. This must necessarily be less than since the carrier must receive some risk loading.

$\varepsilon_j$= risk load percentage for health providers specializing in disease j under scenario II. The total risk percentage over all diseases (weighted by frequency) must necessarily be less than since the gatekeeper must get some risk loading.

$\delta$ = risk load percentage carrier retains

$= \varepsilon - \varepsilon^*$

The values of the conditional probabilities $p_j$ along with $p_j$, $\mu_j$, $\delta_j^2$, $\mu$ and $\delta^2$ are given in Table 6-1.

The risk or financial insolvency for the health provider under each scenario will be defined as the probability that the health provider loses more than R dollars by the end of the year. Gains and losses are accumulated only at the year end so that a health provider actually accruing losses in excess of R in the first six ;months but making up these losses by the end of the year will not be considered insolvent or ruined. Thus, if the average cost over individuals is approximately normally distributed, then the probability of ruin of the health provider is given by the general formula

$$\text{risk} = P_R\left(Z > \frac{\ell + R}{S.D.}\right) \qquad (1)$$

where $\ell$ is the total risk load received by the health provider in addition to the mean cost of care, R is the reserve amount that can be lost without ruin and S.D. is the standard deviation of the health providers total cost. The letter Z represents a standard normal random variable. The values of $\ell$ and S.D. depend upon the risk loading , the population size N and the scenario for reimbursement.

To see how the reimbursement scenarios effect the risk we examine the values of and S.D. under scenario I, the values of load and S.D. for the $i^{th}$ health provider are expected to be

$$\ell_{Ii} = Npt_i \mu c^*$$

$$SD_{Ii} = \sqrt{Npt_i \cdot \Sigma p_j \sigma_j^2}$$

Under scenario II, the values of and S.D. for the $i^{th}$ health provider specializing in the $j^{th}$ disease are expected to be

$$\ell_{IIij} = Npp_j r_{ij} \mu_j c_j$$

$$SD_{IIij} = \sqrt{Npp_j r_{ij} \sigma_j^2}$$

Note that under both scenarios I and II the actual number of patients seen is a binomial random variable distributed about $Npt_i$ and $Npp_j r_{ij}$, respectively. Unlike scenario III where the number of patients seen directly affects the health provider's risk, a change in the number of patients only indirectly changes the risk by multiplying the right hand side of the inequality in the argument of equation (1) by $\frac{\overline{X}}{\sqrt{Npt_i}}$ and $\frac{\overline{X}}{\sqrt{Np_j r_{ij}}}$ respectively, where X is the actual number of patients seen. In the analysis presented here we will assume that under both scenarios I and II, the health provider sees the expected number of patients.

Under scenario III the values for $\ell$ and S.D. for the capitated health provider are

$$\ell_{III} = Np\mu c$$

$$S.D._{III} = \sqrt{N\sigma^2}$$

We note that the three different scenarios result in different expressions for both $\ell$ and S.D. In the next section we will examine the magnitude of these differences. Clearly, the value of R for each health provider will have an impact on the risk of the provider. Also, one would expect the value of R to differ according to the size of the health provider (volume of business) and the specialty. Since it is unclear exactly how the values of R will differ under the various scenarios, we will illustrate the financial risks under the assumption that reserves are zero.

To make comparisons we assume that the total per capita risk load retained by the carrier is the same as that retained by the gatekeeper. Under this assumption, with equal enrolled, the carrier and the gatekeeper are under the same risk of ruin. This assumption may be implemented by setting $\epsilon_j = \epsilon \frac{\mu}{\mu_j}$, for example. With this value for $\epsilon_j$, the total expected load paid to the specialists by the gatekeeper is

$$\text{load}_{II} = \sum_{j=1}^{J} \sum_{i=1}^{k_j} Npp_j \, r_{ij} \, \mu_j \, \epsilon_j \qquad = Np\mu\epsilon^* \cdot \sum_{j=1}^{J} p_j \cdot \sum_{i=1}^{k_j} r_{ij}$$

By definition, both of the last summation terms are equal to one. Hence, total load is

$$\text{load}_{II} = Np\mu\epsilon^*$$

The total load paid to the health providers by the carrier under scenario I is similarly

$$\text{load}_{I} = \sum_{j=1}^{m} Npt_j\mu\epsilon^* \qquad = Np\mu\epsilon^*$$

since

$$\sum_{j=1}^{m} t_j = 1.$$

Recall the load $N_p$ is retained by both the carrier and the gatekeeper. However, in scenario III, the capitated health provider gets both the health provider and the carrier/gatekeeper risk loading. This is reflected in the definition of $L_{III}$, i.e.,

$$L_{IIIi} = Npw_i\mu\epsilon$$

Also, in this case

$$S.D._i = \sqrt{N(pw_i\sigma^2 - (pw_i\mu)^2)}$$

We now wish to compare the risks to the health providers. This is done by substituting the definitions of L and S.D. into equation (1). To simplify the calculations and presentation of material we assume that

$$r_{ij} = \frac{1}{K_j}, \quad t_i = \frac{1}{M} \text{ and } w_i = \frac{1}{L},$$

where L = number of health providers under scenario III. These assumptions mean, essentially, that all health providers are the same size.

## 6.4 DATA

The data used for this analysis are Part B for South Carolina, calendar year 1981. The Part B data were collected from the carrier and are of particular interest because they contain a two digit outpatient diagnosis code. These data also allow separation of inpatient and outpatient physician charges. An indicator of the provider's specialty is also available from these data.

Part A and demographic data are from the Medicare data system. These data cover all persons who had Medicare covered charges in 1981. As with all data containing information that was not used for payment purposes, data quality is open to question. This is particularly true for diagnostic information. Of course, information from a single state may be biased relative to more nationally representative data. The following results should be interpreted with these caveats in mind.

## 6.5 RESULTS

An initial view of the overall level of risk for providers as the number of providers increase under scenario I and II is provided in figures 6-2 and 6-3. Enrollment is held constant at

100,000 individuals for all strategies. As the number of providers increases, the number of patients per provider decreases, and the providers probability of loss increases. This holds for both strategies I and II. The third strategy is more complex. An analysis of this problem was reported in Chapter six, above. It was found that provider risk increases as enrollment increases up to about 70,000 individuals, then the providers' risk declines as enrollment size increases further. Thus, for HMO type organizations there is a "worst" size, but no optimal size. For the purposes of the models, a simpler form was used to model provider capitation, and payments to the risk reserve pool are held constant, in total, for all strategies. Using these assumptions, under strategies I, II, and III, more enrollees always lowers risk for the providers.

As noted earlier, the risk of ruin is offset by a risk loading--a percentage based fee paid to someone in exchange for their accepting a given level of risk. The relationship between the risk loading payment and the number of providers for 100,000 enrollees under the area carrier and HMO strategies is presented in figures 6-4 through 6-8. (This information for the gatekeeper (strategy two) is presented for cardio-vascular disease cases, figure 6-5; for "other disease" cases, figure 6-6; and for "no diagnosis" cases, figure 6-7.)

These figures presented each strategy in isolation. Figures 6-9 through 6-14 compare the strategies with each other. This comparison is done by computing the ratio of the probability of ruin under one strategy to the probability of ruin under another strategy. For example, figure 6-9 is the ratio of the probability of ruin for cardio-vascular disease specialists under area capitation to the probability of ruin for cardio-vascular disease (CVD) specialists under Gatekeeper capitation--as the number of providers increases under each strategy. Remember that the difference between these strategies is that under Gatekeeper capitation, the gatekeeper triages patients. That is, under the gatekeeper model, the CVD specialist is referred only CVD cases. Under area capitation, this physician would treat a more random set of patients, even if he/she is a specialist. Since classification is one way to control risk, one might expect the triage function to also reduce risk. This is not the case for each category, however. As figure 6-9 indicates, the area model is always preferred for the CVD specialty. This is because, while triage does indeed reduce risk, the reduction in this case is small and is offset by other factors. Specifically, CVD cases are expensive on average but highly variable. In addition, CVD represents only about one percent of the total number of persons who actually receive care. When these physicians are allowed a more random sample of cases under area capitation, i.e., not restricted to patients with a diagnosis of CVD, their risk actually declines. The random sample is less variable and lower in cost than CVD type cases. For similar reasons, this result holds also for the other disease categories.

However, as more general classes of patients are considered, the results begin to shift in favor of the gatekeeper model. In figure 6-10, the ruin ratio of the first two strategies are computed for patients with "other" diagnoses--a more nearly random sample. Here, gatekeeper is lower risk if the number of specialists for the gatekeeper is small and the number of providers for the area insurer is large. We are observing the effect of the law of large numbers, in addition to the effect of removing some of the highly variable, but generally costly cases treated by specialist providers.

When the "no diagnosis" category is considered, the results change entirely in favor of the gatekeeper model. As can be seen in figure 6-11, the gatekeeper is always lower risk for providers, strikingly so when the gatekeeper has few specialists relative to the number of practitioners handled by the area insurer. The area model is as much as fifty times more risky for providers under these circumstances. As before, the triage function performed by the gatekeeper has eliminated many of the high variability, high cost cases from this group. The more generalist physicians benefit from this. Since this group represents almost 63% of the people who sought care, this result implies that, overall, the gatekeeper lowers provider risk for most providers; under certain circumstances by very large amounts. Further, it can be demonstrated by reviewing the figures that, if the Gatekeeper can control expenditures by at least one percent over the area insurer, then the gatekeeper would be less risky for providers under all circumstances.

We should note here that one important reason for the relatively poor showing of the gatekeeper strategy for specialists is related to the way that the risk reserve was allocated in the model. The total dollar amount of the reserve is the same for all of the models. This amount was allocated to specialists for strategy two based on differences in means, not differences in variance. The alternative approach (using variance to allocate reserves) is probably more realistic, but it is much more difficult to model, particularly while holding total reserves constant. This problem is worthy of further exploration.

Provider capitation (Strategy III) has yet to be evaluated against the other two models. Considering area capitation first, figure twelve presents the ratio of the probability of ruin under area capitation (strategy one) to the probability of ruin under provider capitation (strategy three). As the figure indicates, provider capitation always entails lower risk for providers. Indeed, when the number of providers under provider capitation is less than the number of providers under area capitation (a closed panel HMO model, for example) the area model can be ten to one hundred times riskier for its providers than direct provider capitation. Remember that the risk reserve amount is constant for all strategies. This means that under provider capitation, the provider receives the payment for accepting risk that the insurer would otherwise have taken. The consequence is that the provider under provider capitation is able to accumulate a larger reserve over one year than would otherwise be possible. In addition, of course, providers under this model also face much higher cost variation than providers under strategies one and two. The result presented in figure 6-12 indicates that the higher reserves completely dominate the additional variation for providers under provider capitation.

Turning next to the Gatekeeper model, figure 6-13 presents the risk ratio (as before) for patients with "other" diagnoses and figure 6-14 presents the risk ratio for patients with no diagnosis. In both cases, provider capitation is clearly the preferred model in terms of risk of ruin. In addition, as in the comparison of provider capitation with area capitation, if the number of providers under the provider model is less than the number of providers under the gatekeeper strategy, then the gatekeeper model inherently contains much more risk for providers than provider capitation.

## 6.6 CONCLUSIONS

These results allow an ordering of the three strategies in terms of their performance along one key dimension: the risk inherent in the strategy for providers. Lowest risk is provider capitation, second is the gatekeeper model (for most providers), and last is area capitation. These results are, of course, dependent on the assumptions that underlie the mathematical expression of these strategies, including the assumption that the gatekeeper and area insurer pay providers on a risk basis somewhat like DRGs.

In addition, there are other critical dimensions that should be considered in evaluating capitation strategy options. For example, area capitation, by definition, entirely obviates the problems of adverse selection and cream skimming. Thus, implementation of this approach does not require adjustments to correct for these problems. Since the ability to adequately adjust for these problems is several years away, at best, this is a significant consideration.

The gatekeeper model would be about as attractive for many providers as provider capitation if the gatekeeper were able to control expenditures by one percent or more. Given the evidence of the success of Medicare's Prospective Payment System in this regard, achieving a one percent reduction in total health care expenditures would not be an unreasonable assumption for the gatekeeper. Thus, the results reported above should not be used to eliminate this strategy from consideration.

Finally, we should note that managing a medical practice under risk would be a new experience for most providers. The overall success of Health Maintenance Organizations is an indication that this is not an impossible task. However, if one were to consider a situation where competition in health care delivery were higher than at present, one possibility is that capitation rates would (in relative terms) be much lower. This implies thin profit margins and a reduced ability for providers to accumulate reserves. This implies that, in addition to the research necessary to support the diverse kinds of capitation arrangements implied by provider capitation, an increased understanding of managing organizations under risk condition will need to be developed.

FIGURE 6-1

*Schematic Diagrams of the Capitation Payment Strategies*

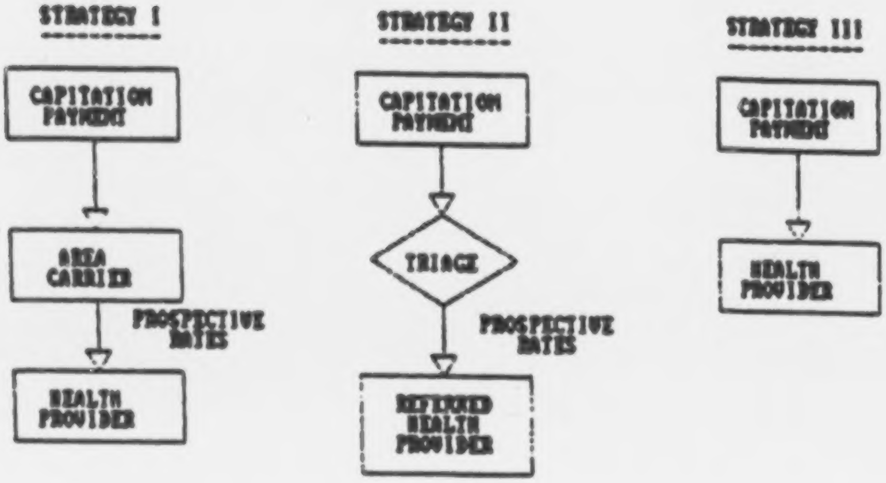
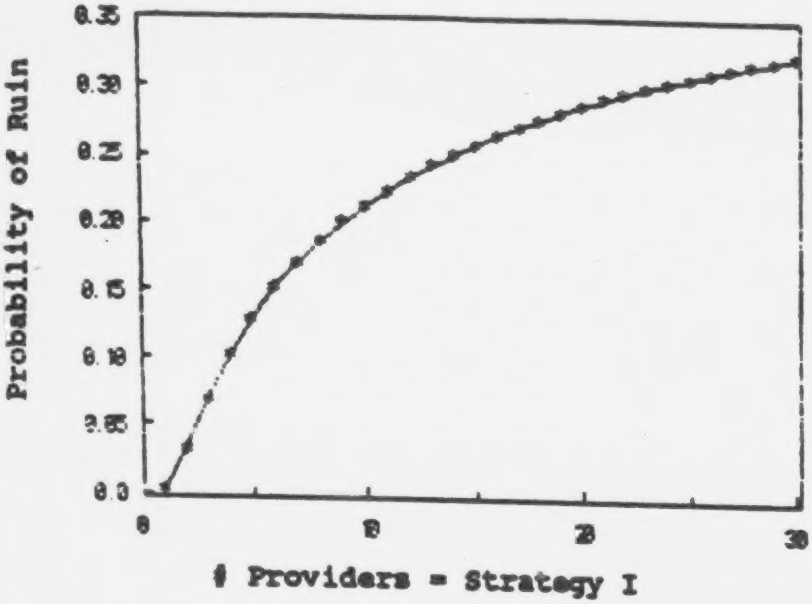

STRATEGY I
CAPITATION PAYMENT
AREA CARRIER
PROSPECTIVE RATES
HEALTH PROVIDER
STRATEGY II
CAPITATION PAYMENT
TRIAGE
PROSPECTIVE RATES
REFERRED HEALTH PROVIDER
STRATEGY III
CAPITATION PAYMENT
HEALTH PROVIDER

**FIGURE 6-2**

***Providers' Risk Under Strategy I, Area Capitation, As the Number of Providers is Increased.****



* Total Enrollment is 100,000 individuals.

FIGURE 6-3

*Providers' Risk Under Strategy II, Gatekeeper, As the Number of Providers Increases.*

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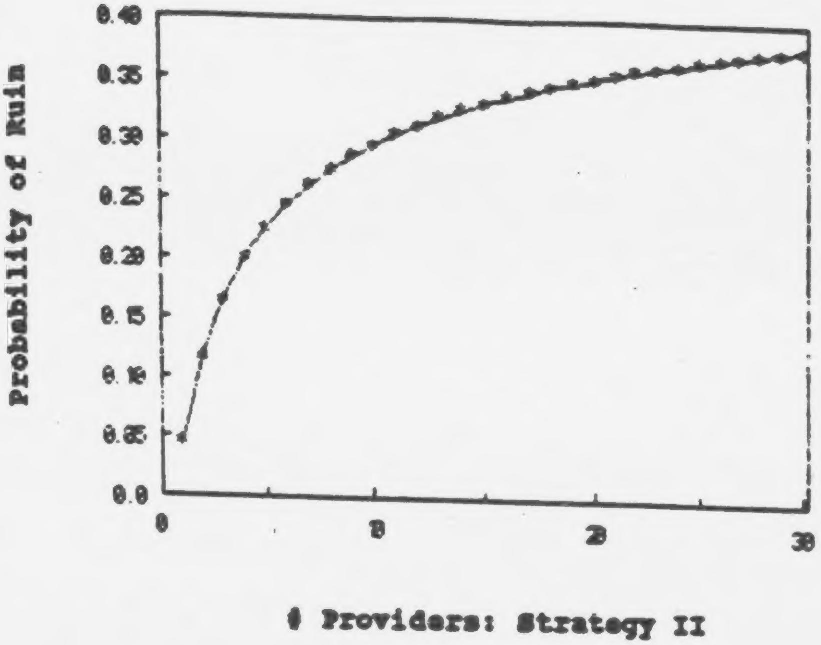
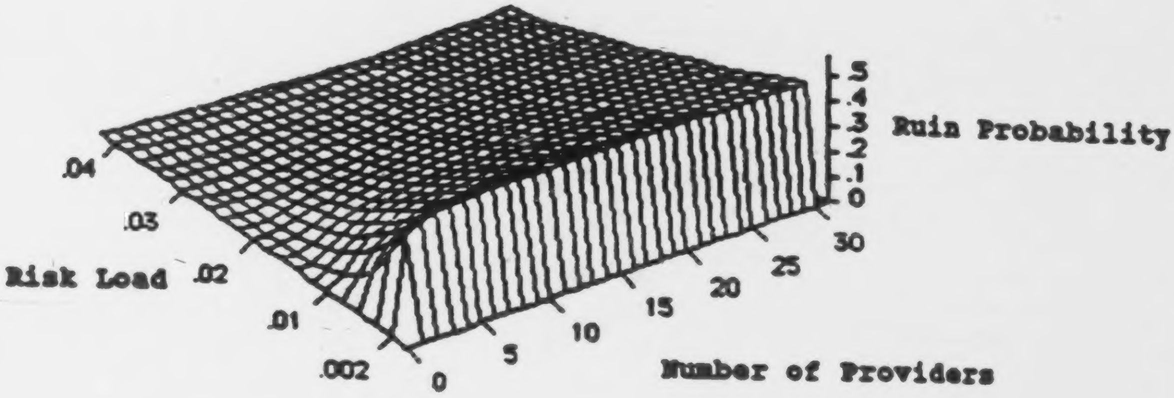


FIGURE 6-4

The Probability of Ruin for Providers Under Area Capitation as Risk Loading and the Number of Providers Change.



# FIGURE 6-5

## *The Probability of Ruin for Cardio-Vascular Disease Specialists Under Gatekeeper Capitation: As Risk Loading and Number of Providers Change.*

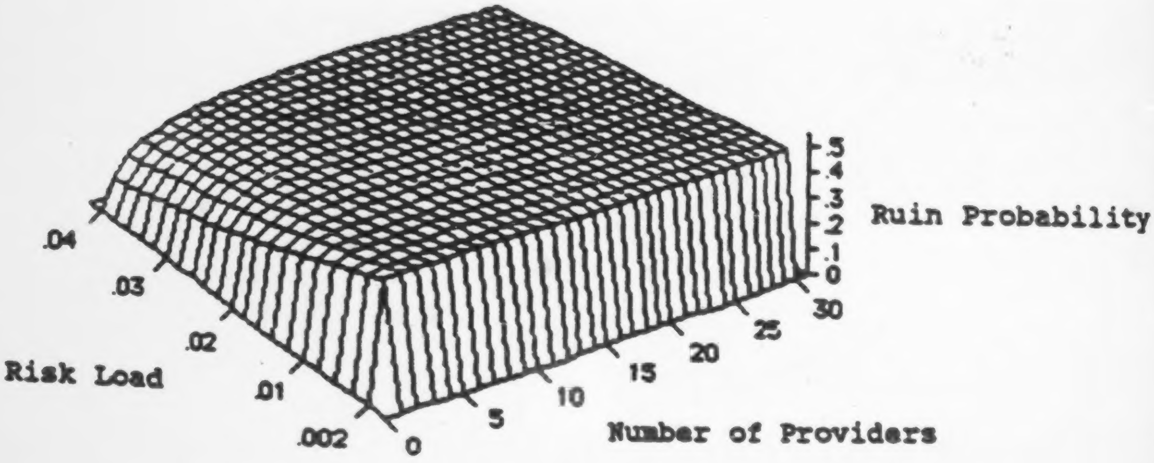


FIGURE 6-6

The Probability of Ruin for Specialist Providers Who Care For "Other" Diseases Under Gatekeeper Capitation As Risk Loading and Number of Providers Change.

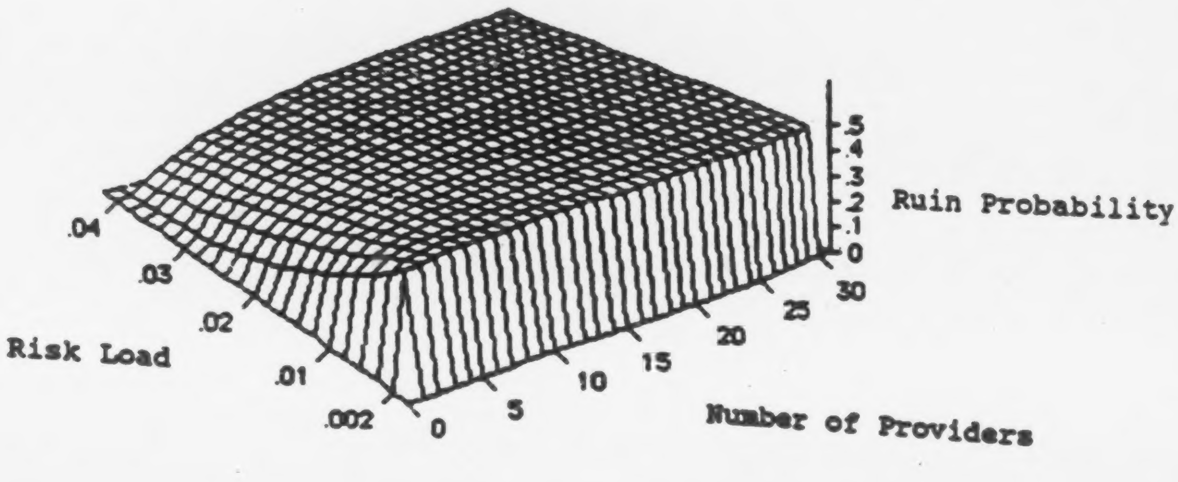


FIGURE 6-7

**The Probability of Ruin for Providers Who Care For "No Diagnosis" Patients Under Gatekeeper Capitation as Risk Loading and Number of Providers Change.**

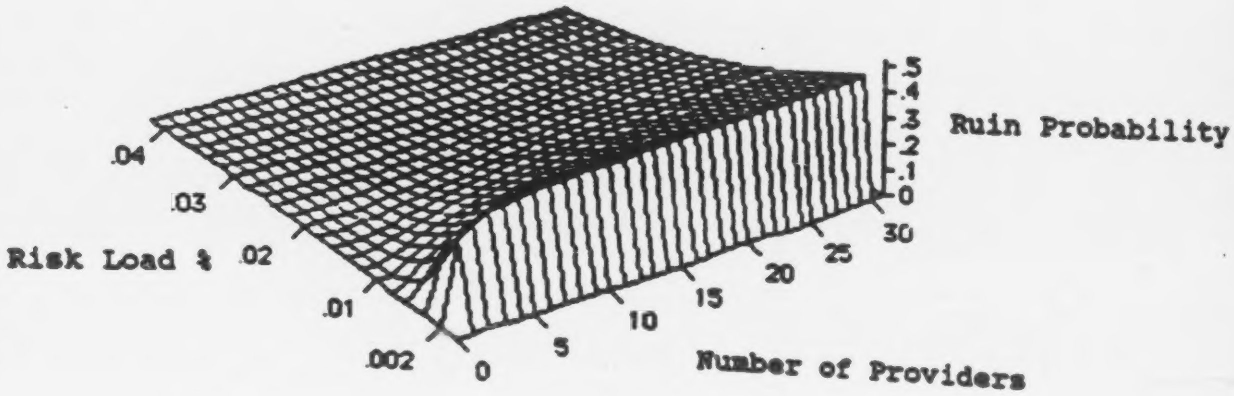
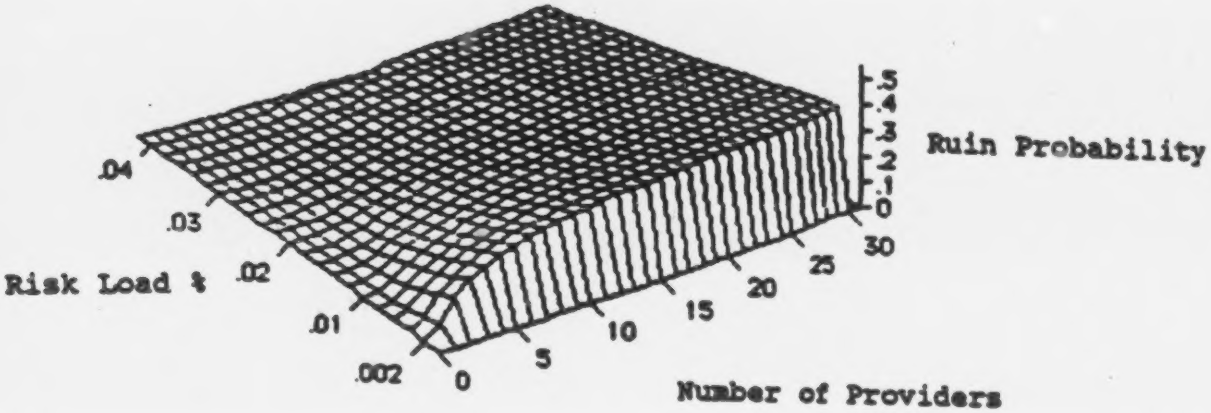


FIGURE 6-8

***The Probability of Ruin for Providers Under Provider Capitation as Risk Loading and Number of Providers Change.***



## FIGURE 6-9

Ratio of the Probability of Ruin Under Area Capitation to the Probability of Ruin Under Gatekeeper Capitation, Cardio-Vascular Disease Cases.

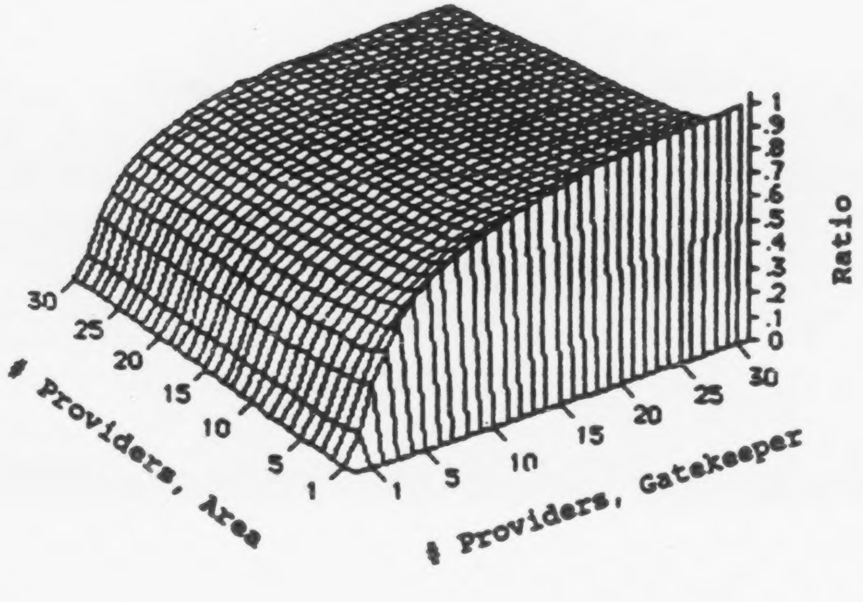
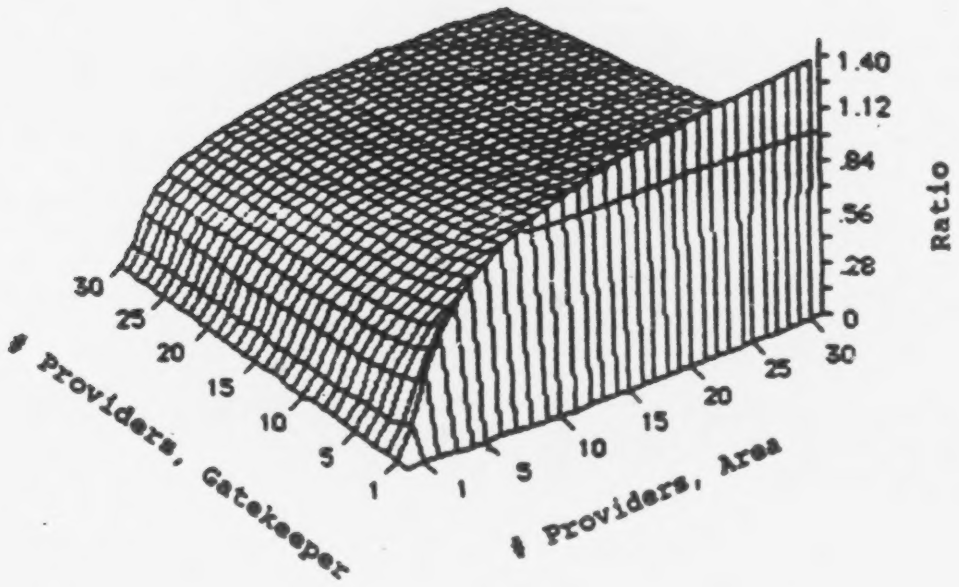


FIGURE 6-10

Ratio of the Probability of Ruin Under Area Capitation to the Probability of Ruin Under Gatekeeper Capitation, "Other" Diagnoses.



## FIGURE 6-11

**Ratio of the Probability of Ruin Under Area Capitation to the Probability of Ruin Under Gatekeeper Capitation, Cases with no Diagnosis.**

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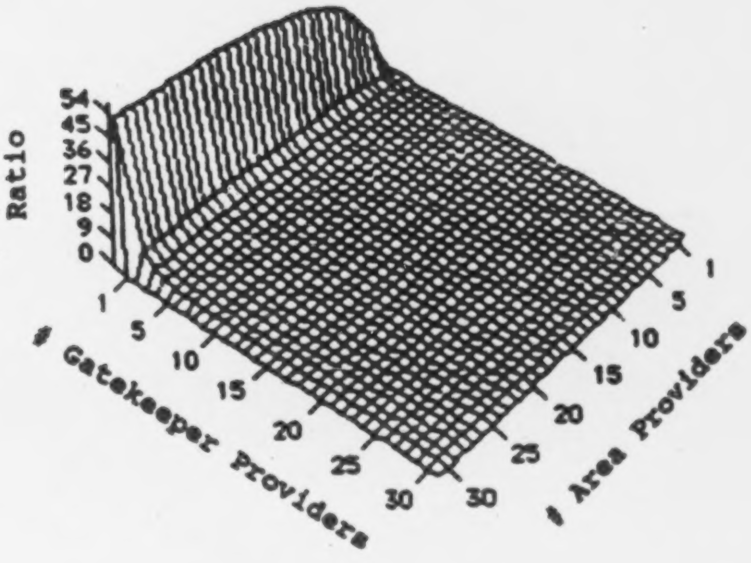


FIGURE 6-12

Ratio of the Probability of Ruin Under Area Capitation to the Probability of Ruin Under Provider Capitation.

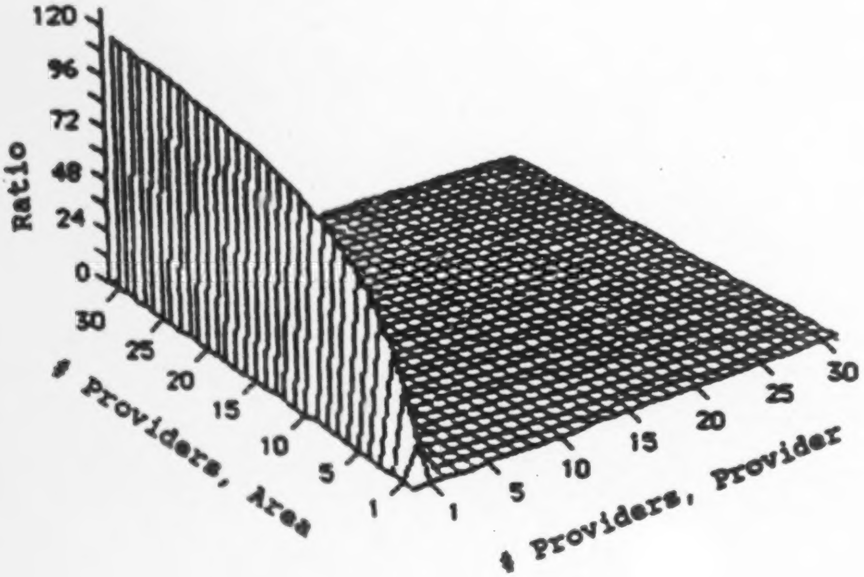


FIGURE 6-13

## Ratio of the Probability of Ruin Under Gatekeeper Capitation to the Probability of Ruin Under Provider Capitation, "Other" Diagnoses

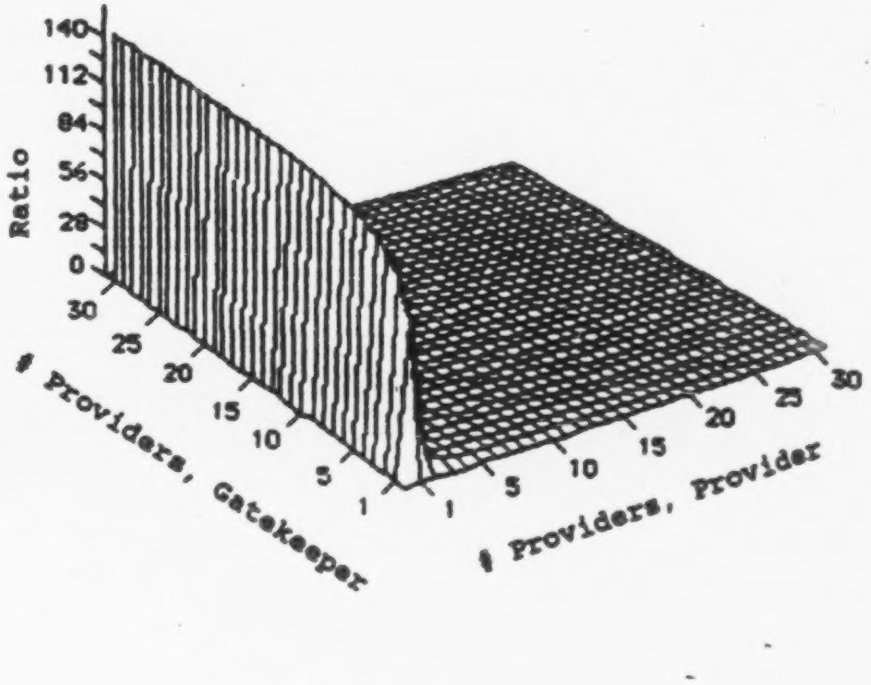
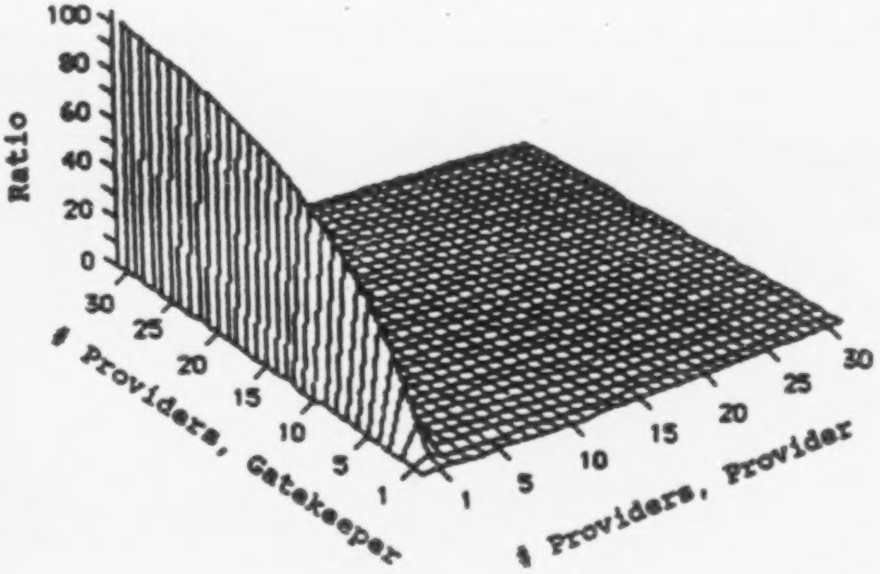


FIGURE 6-14

Ratio of the Probability of Ruin Under Gatekeeper Capitation to the Probability of Ruin Under Provider Capitation; Cases with No Diagnosis.



### Table 6-1

*Overall and Conditional Probability*

| $j$ | | $P_j$ | $u_j$ | $\delta_j^2$ |
|---|---|---|---|---|
| 1 | | .03112 | 2616 | $4.51 \times 10^6$ |
| 2 | | .01030 | 1603 | $3.40 \times 10^6$ |
| 3 | | .09697 | 1675 | $3.70 \times 10^6$ |
| 4 | | .20478 | 1363 | $1.94 \times 10^6$ |
| 5 | | .65682 | 352 | $.367 \times 10^6$ |
| - | OVERALL | .565 | 771 | $1.55 \times 10^6$ |

## CHAPTER SEVEN
## TYPES OF PHYSICIAN PRACTICE AND CAPITATION PAYMENT

### 7.1 INTRODUCTION AND PURPOSE

The purpose of this chapter is to empirically describe types of physician practice. The utility of this description from a policy viewpoint is twofold. First, to the extent that distinctions in practice type are not recognized by a capitated payment system, certain physicians may be systematically advantaged/ disadvantaged. Second, payment systems for other providers, hospitals and nursing homes in particular, have recognized concepts of institutional type in their payment structures. Medicare's teaching adjustment and the urban/rural distinction for hospitals and its distinction between hospital and non-hospital based and between skilled and intermediate care nursing homes are examples. This option for capitation payment has not heretofore been considered in the literature. Our purpose is to open this topic as an area for further discussion. Our hope is to empirically identify types of physician practice and then to determine if these types have different costs per visit and over time. If so, then adjustments at the provider level might be useful in making a capitation system more acceptable to the provider community. The focus is capitation payment for physician and related services only. Partial capitation like this is one way to link hospital DRG payment with risk based payment for other providers. The following sections describe the technique used for for the analysis, the data, and our results.

## 7.2 METHOD

In addition to the statistical properties described in the appendix, GOM may also be used to generated case-mix adjustments for reimbursement strategies. Suppose that we have run a GOM analysis and generate a set of several (K) $g_{ik}$'s for each practice. We can take the estimated $g_{ik}$'s and regress on them a variable like total Medicare payments to a physician or payments per visit. This defines an equation:

$$(13) \quad \text{Expenditures} = B_1 g_{i1} + B_2 g_{i2} + B_3 g_{i3} + B_4 g_{i4} + e_i.$$

In this equation, $B_1$ is the level of out-of-pocket expenditures for persons for whom $g_{i1} = 1.0$. For a practice whose observed characteristics are best predicted as a weighted combination of types two and three (e.g., half type two and half type three), the expenditure level would be $0.5*B_2+0.5*B_3$. Thus, we can get a continuously-adjusted reimbursement level, based upon a few basic dimensions of practice characteristics. Naturally, the case-mix adjustment will depend upon the variables used in the GOM analysis. This rate blending concept has been used with Medicaid data (Vertrees and Manton, 1985) to adjust case-mix reimbursement (i.e., as a multiplier on DRG prices) for specialization of service providers (in this case, to form hospital groups). This technique could be directly introduced into the AAPCC formulation used for Medicare reimbursement for HMO's by viewing the $g_{ik}$ structure as an additional underwriting factor in a probabilistic sense. The use of a probabilistic underwriting factor in the AAPCC has been described and illustrated in Tolley and Manton (1984), where we showed how adjustments could be made to the AAPCC to reflect area-wide health differentials. Such adjustments were evaluated by an independent actuarial group for HCFA (Millman and Robertson, 1983) against other types of health status adjustments, and were found to be both more practical and more resistant to selection bias than traditional AAPCC groups. The GOM model would allow us to extend the probabilistic AAPCC formula to make individual adjustments for detailed health data.

## 7.3 DATA

The data for this analysis are 1981 South Carolina Medicare payment data. The Part B data were of particular interest because they contain a two digit diagnosis code for outpatient visits. Data reliability seems to be typical for data from carriers from this time period. More recent data would be more reliable since Medicare's PPS has made diagnostic information important for payment. However, we should also note that the two digit codes were assigned by the carrier, not be the patient's physician. Data quality limitations will restrict our ability to make fine distinctions. Therefore, better data should result in more distinctions (the K pure types) then we actually found.

## 7.4 RESULTS

Table 7-1 contains the population frequencies and group frequencies for the four pure types. The optimal number of pure groups may be determined empirically. In this case, the optimal number was four. These results are based on forty variables. The first of two earlier runs used only the first five variables in Table One to measure the utility of practice type information alone. The second preliminary run used the next fourteen variables to test the utility of additional information related to the types of services delivered. The utility of adding this information will be evaluated later. First, we describe the four pure types from the full data set.

Pure Type 1: Pure type one consists of general practice, family practice, and internal medicine physicians. These practices' handle large numbers of Medicare bills. The physician makes home visits and trips to nursing homes. He or she treats diabetes, heart disease, hypertension, stroke, pneumonia, and wide variety of conditions. This type represents the potential case managers for capitation at the provider level.

Pure Type 2: Pure type two represents OB-GYN; Opthalmology; Optometry; Urology (i.e., a group of specialties). These physicians have an adequate volume of bills and treat cancer, eye problems, heart disease, urology problems, skin problems, arthritis, and fractures. Per bill charges are higher than for pure type one.

Pure Type 3: This type represents general surgery and radiology. A smaller volume of bills is seen here than for pure types one and two. This type treats a large number of cancer cases, in addition to stroke, circulatory disease, pneumonia, chronic obstructive lung disease, ulcers, and cirrhosis. This type is most likely to accept assignment. Charges here are the highest of any pure type.

Pure Type 4: This type is more diverse, it contains a scattering of specialties (but not surgical). These providers treat the lowest volume of Medicare patients. Interestingly, this is the group that provides treatment for mental and drug abuse problems. Charges for this pure type are the lowest, in general, of any pure type. These physicians are also potential case managers for certain types of cases.

These descriptions are based on the forty internal variables GOM run. As noted earlier, two earlier runs were also done using only five and nineteen internal variables respectively. In order to assess the utility of the additional information (from five to nineteen to forty), twelve blended rate regressions (as described in the Method section, above) were estimated--one for each of the GOM runs. These independent variables were run against total part B costs and per visit costs, logged and unlogged. That is, total and per visit costly were the dependent variables in an ordinary least squares regression. The $r^2$ statistics for these regressions are presented in Table Two. The $r^2$ statistic measures the ability of the pure types to account for variation in the dependent variable. The higher $r^2$ for the logged dependent variables indicates that both of the dependent variables are more nearly log-normally distributed than normally distributed. In other words, the distribution is more highly peaked than normal and has a long tail. Lognormal distributions are common for economic data because, while prices cannot be negative, they can be very high. Thus, this is not an unusual finding.

Nineteen variables clearly improves the explanatory power of the regression. Adding twenty one pieces of diagnostic information slightly improves the explanatory power for the logged Part B regression, but not for the others. This implies that per visit costs vary by type of practice and services offered, but not systematically by patient diagnosis. Patient diagnosis affects overall charges for a year but this information is less important than practice type and service availability.

Table 7-2 presents the regression coefficients for the forty variables GOM pure types. For the logged version, the anti-log of the coefficients is in parentheses.

## TABLE 7-2

*Regression Coefficients (40 Variables GOM)*

| Pure | No Log |  | Log |  |
|---|---|---|---|---|
| Type | Total | Per Visit | Total | Per Visit |
| Pt.1 | 48,900 | 7.85 | 10.56(38,561) | 3.06 (21.33) |
| Pt.2 | 84,926 | 140.62 | 10.95(56,954) | 4.84(126.47) |
| Pt.3 | 114,176 | 181.34 | 11.17(70,969) | 4.96(142.59) |
| Pt.4 | -18,950 | 62.70 | 4.49 (89.12) | 3.35 (28.50) |
| $R^2$ | 12.2% | 14.40% | 75.50% | 36.5% |

Here, we can see the general surgery (radiology) group (Pure type three) with a large volume of cancer cases has the greatest total ($70,969) and per bill ($142.59) costs. Group 1 (general practice) has very low per bill charges ($21.33) but a large volume of bills. Group 2, general specialties, has high per visit charges ($126.47) and high volume for a large total bill. Group4 (includes psychiatry) has both low volume and low charges. The GOM model explains more variation in this case partly because there is more variation to be explained.

## 7.5 CONCLUSION

These coefficient values are quite different from each other. Thus, if used to adjust rates, they would reduce monies transferred across practice types by approximately the percentages given by the $r^2$ statistic--assuming that the distribution of patient visits maintains its current pattern. Thus, there may be some utility in an approach like this for adjusting physician (i.e., Part B) capitation rates. We do not wish to imply that the variables we have used or the way we have used these variables is the only possible approach. Our purpose was to test whether this approach--at the physician level--might prove useful--as it has for hospitals and nursing homes. These results indicate that adjusting rates for different practice types may well be a fruitful approach toward a capitation system at the provider level that is more feasible to implement because it redistributes less money across physician types. If this is not done and if patient level service need prediction remains at about its present level of accuracy (1-4%), then the losers will tend to be surgeons and related specialties, and the specialists who treat complex cases, i.e., pure types three and two. This may not be an undesirable outcome, particularly given the great differences in income between these physicians and their more generalist colleagues. However, given its potential cost, a decision to transfer money in this way should be made explicitly.

## TABLE 7-1

## GOM MARGINAL FREQUENCIES
## FOUR PURE TYPES: PHYSICIAN PRACTICES

PRACTICE TYPE VARIABLES

| | Average Frequency | Marginal Frequency <---Group---> | | | |
|---|---|---|---|---|---|
| | | I | II | III | IV |
| **I. PROVIDER TYPE** | | | | | |
| Hospital Based | 0.9339 | 0.9857 | 1.0000 | 0.9977 | 0.7900 |
| Group | 0.0358 | 0.0000 | 0.0000 | 0.0000 | 0.1227 |
| Other | 0.0303 | 0.0143 | 0.0000 | 0.0023 | 0.0873 |
| H = 0.2823 QRF | | 0.9951 | 1.0059 | 1.0282 | 0.9872 |
| **2. SPECIALTY** | | | | | |
| General Practice | 0.1790 | 0.4400 | 0.0000 | 0.0000 | 0.1437 |
| General Surgery | 0.0787 | 0.0000 | 0.0000 | 0.5248 | 0.0000 |
| Family Practice | 0.1076 | 0.2608 | 0.0000 | 0.0000 | 0.0909 |
| Internal Medicine | 0.1229 | 0.2992 | 0.0000 | 0.0000 | 0.1023 |
| Obstetrics and Gynecology | 0.0756 | 0.0000 | 0.2118 | 0.0000 | 0.0734 |
| Ophthalmology | 0.0369 | 0.0000 | 0.1393 | 0.0000 | 0.0000 |
| Orthapedic Surgery | 0.0369 | 0.0000 | 0.1393 | 0.0000 | 0.0000 |
| Pathology | 0.0129 | 0.0000 | 0.0000 | 0.0178 | 0.0386 |
| Psychiatry | 0.0411 | 0.0000 | 0.0000 | 0.0000 | 0.1551 |
| Radiology | 0.0296 | 0.0000 | 0.0000 | 0.1724 | 0.0141 |
| Urology | 0.0310 | 0.0000 | 0.1169 | 0.0000 | 0.0000 |
| Other | 0.2479 | 0.0000 | 0.3927 | 0.2850 | 0.3818 |
| **3. NUMBER OF PROVIDERS** | | | | | |
| Only 1 | 0.0913 | 0.0814 | 0.1083 | 0.2235 | 0.0309 |
| 2-5 | 0.0996 | 0.1296 | 0.1690 | 0.1190 | 0.0000 |
| 6+ | 0.0132 | 0.0000 | 0.0160 | 0.0715 | 0.0000 |
| NA | 0.7959 | 0.7889 | 0.7066 | 0.5860 | 0.9691 |
| H = 0.3647 QRF | | 0.9968 | 1.0182 | 0.9393 | 1.0153 |
| **4. BOARD CERTIFIED** | | | | | |
| Certified | 0.4133 | 0.5445 | 0.4126 | 0.2288 | 0.3612 |
| Non-Certified | 0.5867 | 0.4555 | 0.5874 | 0.7712 | 0.6388 |
| H = 0.1160 QRF | | 0.9927 | 1.0098 | 1.0033 | 0.9979 |

5. NUMBER BILLS

| | | | | | |
|---|---|---|---|---|---|
| To 35 | 0.2521 | 0.0000 | 0.0000 | 0.0000 | 0.9101 |
| To 301 | 0.2479 | 0.0000 | 0.4550 | 0.6933 | 0.0899 |
| To 1006 | 0.2503 | 0.4072 | 0.3733 | 0.1892 | 0.0000 |
| To 2387 | 0.1498 | 0.3569 | 0.1183 | 0.0459 | 0.0000 |
| 2388 + | 0.0999 | 0.2358 | 0.0534 | 0.0716 | 0.0000 |
| H = 2.7338 QRF | | 1.0214 | 0.9305 | 1.2238 | 0.9356 |

6. OFFICE

| | | | | | |
|---|---|---|---|---|---|
| Here | 0.8894 | 1.0000 | 1.0000 | 0.8749 | 0.6555 |
| Not Here | 0.1106 | 0.0000 | 0.0000 | 0.1251 | 0.3445 |
| H = 0.4268 QRF | | 1.0437 | 1.0891 | 0.8536 | 0.9434 |

7. HOME

| | | | | | |
|---|---|---|---|---|---|
| Here | 0.2347 | 0.7573 | 0.0000 | 0.0000 | 0.0000 |
| Not Here | 0.7653 | 0.2427 | 1.0000 | 1.0000 | 1.0000 |
| H = 1.4109 QRF | | 0.9913 | 0.9791 | 1.0689 | 0.9959 |

8. INPATIENT

| | | | | | |
|---|---|---|---|---|---|
| Here | 0.7666 | 0.9635 | 1.0000 | 1.0000 | 0.1825 |
| Not Here | 0.2334 | 0.0365 | 0.0000 | 0.0000 | 0.8175 |
| H = 1.4469 QRF | | 0.9072 | 1.2013 | 1.0050 | 0.9215 |

9. NURSING FACILITIES

| | | | | | |
|---|---|---|---|---|---|
| Here | 0.2472 | 0.7065 | 0.1184 | 0.0000 | 0.0000 |
| Not Here | 0.7528 | 0.2935 | 0.8816 | 1.0000 | 1.0000 |
| H = 1.0855 QRF | | 0.9828 | 0.9922 | 0.9659 | 1.0405 |

10. OUTPATIENT

| | | | | | |
|---|---|---|---|---|---|
| Here | 0.5513 | 0.8980 | 1.0000 | 1.0000 | 0.0000 |
| Not Here | 0.4487 | 0.1020 | 0.0000 | 0.0000 | 1.0000 |
| H = 2.2793 QRF | | 0.8715 | 0.7618 | 0.8251 | 1.4217 |

### 11. LAB

| | | | | | |
|---|---|---|---|---|---|
| Here | 0.4026 | 1.0000 | 0.1935 | 0.0000 | 0.2002 |
| Not Here | 0.5974 | 0.0000 | 0.8065 | 1.0000 | 0.7998 |
| H = 1.6187 QRF | | 0.9473 | 0.9354 | 1.2200 | 1.0114 |

### 12. OTHER

| | | | | | |
|---|---|---|---|---|---|
| Here | 0.0596 | 0.0612 | 0.0988 | 0.0619 | 0.0231 |
| Not Here | 0.9404 | 0.9388 | 0.9012 | 0.9381 | 0.9769 |
| H = 0.0269 | | 0.9978 | 1.0030 | 0.9946 | 1.0022 |

### 13. MEDICAL SERVICES

| | | | | | |
|---|---|---|---|---|---|
| Provided | 0.8610 | 1.0000 | 1.0000 | 0.8423 | 0.5572 |
| Not Provided | 0.1390 | 0.0000 | 0.0000 | 0.1577 | 0.4428 |
| H = 0.5713 QRF | | 1.0648 | 1.0935 | 0.8374 | |
| 0.9248 | | | | | |

### 14. SURGERY

| | | | | | |
|---|---|---|---|---|---|
| Provided | 0.6949 | 1.0000 | 1.0000 | 0.8019 | 0.0000 |
| Not Provided | 0.3051 | 0.0000 | 0.0000 | 0.1981 | 1.0000 |
| H = 1.944 QRF | | 0.9813 | 1.1738 | 0.8052 | 0.9580 |

### 15. CONSULT

| | | | | | |
|---|---|---|---|---|---|
| Provided | 0.5374 | 0.6780 | 1.0000 | 0.4309 | 0.0000 |
| Not Provided | 0.4626 | 0.3220 | 0.0000 | 0.5691 | 1.0000 |
| H = 1.4555 QRF | | 0.9304 | 1.1613 | 0.7314 | 1.0563 |

### 16. X-RAY

| | | | | | |
|---|---|---|---|---|---|
| Provided | 0.2743 | 0.5054 | 0.3713 | 0.1753 | 0.0000 |
| Not Provided | 0.7257 | 0.4946 | 0.6287 | 0.8247 | 1.0000 |
| H = 0.4890 QRF | | 0.9932 | 0.9758 | 1.0335 | 1.0129 |

17. ASSIST SURGERY

| | | | | | |
|---|---|---|---|---|---|
| Provided | 0.6741 | 1.0000 | 0.7371 | 0.4671 | 0.3065 |
| Not Provided | 0.3259 | 0.0000 | 0.2629 | 0.5329 | 0.6935 |
| H = 0.7766 QRF | | 1.1394 | 0.9378 | 0.7840 | 1.0050 |

18. AMB SURGERY

| | | | | | |
|---|---|---|---|---|---|
| Provided | 0.4105 | 0.7409 | 0.4516 | 0.6829 | 0.0000 |
| Not Provided | 0.5895 | 0.2591 | 0.5484 | 0.3171 | 1.0000 |
| H = 0.9073 QRF | | 0.9427 | 0.9265 | 0.9215 | 1.160 |

19. OTHER SERVICE

| | | | | | |
|---|---|---|---|---|---|
| Provided | 0.4532 | 1.0000 | 0.1595 | 0.3685 | 0.1837 |
| Not Provided | 0.5468 | 0.0000 | 0.8405 | 0.6315 | 0.8163 |
| H = 1.1621 QRF | | 0.9842 | 1.0105 | 0.9847 | 1.0146 |

20. INFECTIOUS-PARASITIC DISEASES

| | | | | | |
|---|---|---|---|---|---|
| To 1.05 | 0.5000 | 0.0973 | 0.5300 | 0.7573 | 0.7738 |
| To 4.83 | 0.2500 | 0.4707 | 0.2833 | 0.2427 | 0.0000 |
| To 10.47 | 0.1501 | 0.3600 | 0.1531 | 0.0000 | 0.0000 |
| 10.48 + | 0.0999 | 0.0720 | 0.0336 | 0.0000 | 0.2262 |
| H = 1.2926 QRF | | 1.0046 | 0.9443 | 1.0255 | 1.0318 |

21. CANCER

| | | | | | |
|---|---|---|---|---|---|
| To 0.62 | 0.5000 | 0.0973 | 0.5300 | 0.7573 | 0.7738 |
| To 4.38 | 0.2500 | 0.4707 | 0.2833 | 0.2427 | 0.0000 |
| To 10.47 | 0.1501 | 0.3600 | 0.1531 | 0.0000 | 0.0000 |
| 10.48 + | 0.0999 | 0.0720 | 0.0336 | 0.0000 | 0.2262 |
| H = 1.2926 QRF | | 1.0046 | 0.9443 | 1.0255 | 1.0318 |

22. DIABETES

| | | | | | |
|---|---|---|---|---|---|
| To 0.08 | 0.5000 | 0.0000 | 0.8897 | 0.0259 | 0.9391 |
| To 7.14 | 0.2500 | 0.3046 | 0.1103 | 0.9741 | 0.0000 |
| To 22.24 | 0.2001 | 0.5968 | 0.0000 | 0.0000 | 0.0000 |
| 22.29 + | 0.0499 | 0.0986 | 0.0000 | 0.0000 | 0.0000 |
| H = 3.0543 QRF | | 1.0721 | 1.0372 | 0.9020 | 0.9363 |

23. MENT. DRUGS

| | | | | | |
|---|---|---|---|---|---|
| To 0.30 | 0.5000 | 0.0000 | 0.9633 | 0.1643 | 0.7959 |
| To 6.40 | 0.4001 | 1.0000 | 0.0367 | 0.5377 | 0.0000 |
| To 50.00 | 0.0506 | 0.0000 | 0.0000 | 0.2980 | 0.0357 |
| 50.58 + | 0.0492 | 0.0000 | 0.0000 | 0.0000 | 0.1684 |
| H = 2.5288 QRF | | 1.0179 | 0.9925 | 0.9995 | 0.9878 |

24. EYE PROBLEMS

| | | | | | |
|---|---|---|---|---|---|
| To 0.77 | 0.9001 | 1.0000 | 0.8914 | 0.6544 | 0.9207 |
| To 65.96 | 0.0499 | 0.0000 | 0.0000 | 0.3456 | 0.0000 |
| 67.39 + | 0.0499 | 0.0000 | 0.1086 | 0.0000 | 0.0793 |
| H = 0.6983 QRF | | 1.0168 | 0.9696 | 1.0709 | 0.9763 |

25. HEART

| | | | | | |
|---|---|---|---|---|---|
| To 0.09 | 0.2500 | 0.0000 | 0.1715 | 0.0000 | 0.7719 |
| To 8.26 | 0.2500 | 0.0000 | 0.6720 | 0.5859 | 0.0000 |
| To 21.49 | 0.2500 | 0.5120 | 0.0572 | 0.4141 | 0.0003 |
| To 56.57 | 0.2001 | 0.4880 | 0.0000 | 0.0000 | 0.1308 |
| 56.76 + | 0.0499 | 0.0000 | 0.0993 | 0.0000 | 0.0970 |
| H = 2.9709 QRF | | 1.0788 | 0.9290 | 1.1383 | 0.9153 |

26. HYPERTENSION

| | | | | | |
|---|---|---|---|---|---|
| To 0.15 | 0.5000 | 0.0000 | 0.8392 | 0.2827 | 0.9191 |
| To 8.44 | 0.2500 | 0.3508 | 0.1608 | 0.7173 | 0.0000 |
| To 17.51 | 0.1501 | 0.4270 | 0.0000 | 0.0000 | 0.0000 |
| 17.58 + | 0.0999 | 0.2222 | 0.0000 | 0.0000 | 0.0809 |
| H = 2.2439 QRF | | 1.1244 | 1.0216 | 0.8735 | 0.9075 |

27. STROKE

| | | | | | |
|---|---|---|---|---|---|
| To 1.26 | 0.7500 | 0.3908 | 1.0000 | 0.5346 | 0.9756 |
| To 3.51 | 0.1501 | 0.4409 | 0.0000 | 0.1556 | 0.0000 |
| To 6.38 | 0.0499 | 0.1230 | 0.0000 | 0.1004 | 0.0000 |
| 6.41 + | 0.0499 | 0.0453 | 0.0000 | 0.2094 | 0.0244 |
| H = 1.0484 QRF | | 0.9299 | 1.0581 | 1.0453 | 1.0032 |

### 28. CIRCULATORY DISEASE

| | | | | | |
|---|---|---|---|---|---|
| To 0.22 | 0.5000 | 0.0000 | 0.8894 | 0.0000 | 1.0000 |
| To 2.54 | 0.2500 | 0.6243 | 0.1106 | 0.2032 | 0.0000 |
| To 11.16 | 0.2001 | 0.3757 | 0.0000 | 0.5012 | 0.0000 |
| 11.18 + | 0.0499 | 0.0000 | 0.0000 | 0.2957 | 0.0000 |
| H = 2.8672 QRF | | 0.9825 | 0.8433 | 1.2516 | 1.0395 |

### 29. PNEUMONIA

| | | | | | |
|---|---|---|---|---|---|
| To 0.57 | 0.7500 | 0.3836 | 1.0000 | 0.4290 | 1.0000 |
| To 2.87 | 0.2001 | 0.6164 | 0.0000 | 0.1954 | 0.0000 |
| 2.89 + | 0.0499 | 0.0000 | 0.0000 | 0.3756 | 0.0000 |
| H = 1.5255 QRF | | 0.9032 | 1.1066 | 0.9853 | 1.0167 |

### 30. COLUNG DISEASE

| | | | | | |
|---|---|---|---|---|---|
| To 0.20 | 0.5000 | 0.0000 | 1.0000 | 0.0000 | 0.9470 |
| To 3.44 | 0.2500 | 0.5190 | 0.0000 | 0.5081 | 0.0000 |
| To 9.79 | 0.2001 | 0.4810 | 0.0000 | 0.2688 | 0.0000 |
| 9.81 + | 0.0499 | 0.0000 | 0.0000 | 0.2231 | 0.0530 |
| H = 2.8759 QRF | | 1.0500 | 0.9060 | 1.1614 | 0.9550 |

### 31. ULCERS

| | | | | | |
|---|---|---|---|---|---|
| To 1.57 | 0.7500 | 0.5410 | 1.0000 | 0.1174 | 1.0000 |
| To 6.45 | 0.2001 | 0.4590 | 0.0000 | 0.4985 | 0.0000 |
| 6.51 + | 0.0499 | 0.0000 | 0.0000 | 0.3841 | 0.0000 |
| H = 1.8007 QRF | | 0.9425 | 1.0716 | 0.9635 | 1.0154 |

### 32. ABDOMINAL PAIN

| | | | | | |
|---|---|---|---|---|---|
| To 0.17 | 0.5000 | 0.0000 | 1.0000 | 0.0000 | 0.9840 |
| To 2.57 | 0.2500 | 0.7268 | 0.0000 | 0.0000 | 0.0000 |
| To 12.14 | 0.2001 | 0.2732 | 0.0000 | 0.7009 | 0.0000 |
| 12.26 + | 0.0499 | 0.0000 | 0.0000 | 0.2991 | 0.0160 |
| H = 3.6161 QRF | | 1.1001 | 0.8295 | 1.1217 | 0.9864 |

33. CIRRHOSIS

| | | | | | |
|---|---|---|---|---|---|
| To 0.82 | 0.7500 | 0.6403 | 1.0000 | 0.0000 | 1.0000 |
| To 2.92 | 0.1501 | 0.3597 | 0.0000 | 0.2903 | 0.0000 |
| To 5.22 | 0.0499 | 0.0000 | 0.0000 | 0.3548 | 0.0000 |
| 5.25 + | 0.0499 | 0.0000 | 0.0000 | 0.3548 | 0.0000 |
| H = 2.3715 QRF | | 0.9717 | 0.9620 | 1.0430 | 1.0432 |

34. RENAL P.

| | | | | | |
|---|---|---|---|---|---|
| To 0.47 | 0.5003 | 0.0000 | 0.8569 | 0.0000 | 0.9627 |
| To 4.34 | 0.2497 | 0.6149 | 0.0000 | 0.4260 | 0.0000 |
| To 29.87 | 0.2001 | 0.3851 | 0.0000 | 0.5740 | 0.0000 |
| 30.77 + | 0.0499 | 0.0000 | 0.1431 | 0.0000 | 0.0373 |
| H = 2.8699 QRF | | 0.9833 | 1.0839 | 1.0543 | 0.9203 |

35. SKIN P.

| | | | | | |
|---|---|---|---|---|---|
| To 0.23 | 0.5000 | 0.0048 | 0.7424 | 0.0000 | 1.0000 |
| To 1.89 | 0.2500 | 0.6437 | 0.0970 | 0.2436 | 0.0000 |
| To 15.94 | 0.2001 | 0.3515 | 0.0000 | 0.6889 | 0.0000 |
| 16.32 + | 0.0499 | 0.0000 | 0.1607 | 0.0675 | 0.0000 |
| H = 2.7329 QRF | | 0.9528 | 0.9855 | 1.0259 | 1.0506 |

36. ARTHRITIS

| | | | | | |
|---|---|---|---|---|---|
| To 0.51 | 0.5003 | 0.0000 | 0.8772 | 0.0000 | 0.9420 |
| To 4.97 | 0.2497 | 0.4129 | 0.0000 | 1.0000 | 0.0000 |
| To 17.09 | 0.2001 | 0.5871 | 0.0000 | 0.0000 | 0.0000 |
| 17.14 + | 0.0499 | 0.0000 | 0.1228 | 0.0000 | 0.0580 |
| H = 3.4351 QRF | | 1.0899 | 1.0858 | 0.8074 | 0.9186 |

37. JOINT P.

| | | | | | |
|---|---|---|---|---|---|
| To 0.18 | 0.5000 | 0.0000 | 0.8245 | 0.0000 | 0.9839 |
| To 1.90 | 0.2500 | 0.6854 | 0.0000 | 0.2730 | 0.0000 |
| To 14.46 | 0.2001 | 0.3146 | 0.0000 | 0.7270 | 0.0000 |
| 14.46 + | 0.0499 | 0.0000 | 0.1755 | 0.0000 | 0.0161 |
| H = 3.0764 QRF | | 0.9859 | 1.0051 | 1.0508 | 0.9873 |

### 38. SYMPTOMS

| | | | | | |
|---|---|---|---|---|---|
| To 1.58 | 0.5000 | 0.1563 | 0.7448 | 0.2485 | 0.8204 |
| To 5.91 | 0.2500 | 0.5584 | 0.1538 | 0.2195 | 0.0000 |
| To 20.00 | 0.2004 | 0.2853 | 0.1014 | 0.4758 | 0.0322 |
| 20.19 + | 0.0496 | 0.0000 | 0.0000 | 0.0562 | 0.1474 |
| H = 1.2448 QRF | | 1.0119 | 0.9684 | 1.1859 | 0.9301 |

### 39. FRACTURE

| | | | | | |
|---|---|---|---|---|---|
| To 0.00 | 0.5205 | 0.0000 | 0.8322 | 0.0000 | 0.9756 |
| To 1.08 | 0.2299 | 0.7289 | 0.0000 | 0.0000 | 0.0000 |
| To 11.04 | 0.1997 | 0.2711 | 0.0000 | 1.0000 | 0.0000 |
| 11.11 + | 0.0499 | 0.0000 | 0.1678 | 0.0000 | 0.0244 |
| H = 3.7244 QRF | | 1.0087 | 0.9800 | 0.8465 | 1.0781 |

### 40. RESIDUAL

| | | | | | |
|---|---|---|---|---|---|
| To 7.40 | 0.5000 | 0.3670 | 0.5355 | 0.0000 | 0.8485 |
| To 14.41 | 0.2500 | 0.5375 | 0.0522 | 0.5255 | 0.0000 |
| To 40.74 | 0.1501 | 0.0955 | 0.1607 | 0.4745 | 0.0448 |
| 40.91 + | 0.0999 | 0.0000 | 0.2516 | 0.0000 | 0.1067 |
| H = 1.7911 QRF | | 0.9818 | 1.0830 | 0.9941 | 0.9500 |

### 41. % MALE

| | | | | | |
|---|---|---|---|---|---|
| To 0.00 | 0.1383 | 0.0000 | 0.0785 | 0.0000 | 0.4426 |
| To 25.30 | 0.1117 | 0.1436 | 0.1369 | 0.0000 | 0.1106 |
| To 45.00 | 0.5003 | 0.8306 | 0.4486 | 0.6049 | 0.0870 |
| To 58.21 | 0.1501 | 0.0254 | 0.2156 | 0.3856 | 0.1087 |
| 58.29 + | 0.0995 | 0.0004 | 0.1204 | 0.0095 | 0.2512 |
| H = 1.4602 QRF | | 1.0470 | 1.0005 | 1.1046 | 0.9023 |

### 42. % ASSIGNED

| | | | | | |
|---|---|---|---|---|---|
| To 0.00 | 0.1467 | 0.0083 | 0.0065 | 0.0000 | 0.5431 |
| To 8.42 | 0.1033 | 0.2245 | 0.0935 | 0.0124 | 0.0095 |
| To 38.60 | 0.2500 | 0.3832 | 0.3913 | 0.0715 | 0.0224 |
| To 83.33 | 0.2500 | 0.3265 | 0.3360 | 0.2568 | 0.0590 |
| To 99.97 | 0.1498 | 0.0575 | 0.1702 | 0.5647 | 0.0335 |
| 100.00 + | 0.1002 | 0.0000 | 0.0025 | 0.0947 | 0.3325 |
| H = 2.1366 QRF | | 1.0369 | 1.1017 | 0.9756 | 0.8841 |

### 43. PB CHARGE

| | | | | | |
|---|---|---|---|---|---|
| To 22.84 | 0.2500 | 0.3826 | 0.0000 | 0.0243 | 0.4544 |
| To 39.73 | 0.2500 | 0.4555 | 0.0646 | 0.1366 | 0.2502 |
| To 97.44 | 0.2500 | 0.1619 | 0.4405 | 0.1936 | 0.1801 |
| To 196.39 | 0.1501 | 0.0000 | 0.3774 | 0.2344 | 0.0531 |
| 197.82 + | 0.0999 | 0.0000 | 0.1175 | 0.4111 | 0.0622 |
| H = 1.5205 QRF | | 1.0338 | 1.1113 | 0.8922 | 0.9172 |

### 44. T-CHARGE

| | | | | | |
|---|---|---|---|---|---|
| To 203 | 0.2500 | 0.0000 | 0.0056 | 0.0000 | 0.8495 |
| To 1671 | 0.2500 | 0.2635 | 0.3427 | 0.2711 | 0.1453 |
| To 5058 | 0.2500 | 0.4353 | 0.2417 | 0.3585 | 0.0052 |
| To 17467 | 0.2001 | 0.2658 | 0.3084 | 0.2750 | 0.0000 |
| 17522 + | 0.0499 | 0.0353 | 0.1016 | 0.0954 | 0.0000 |
| H = 1.8436 QRF | | 1.0179 | 0.9874 | 1.0079 | 0.9884 |

### 45. INDICATE

| | | | | | |
|---|---|---|---|---|---|
| 01,08,16 | 0.3606 | 0.6990 | 0.1128 | 0.0000 | 0.3724 |
| 02 | 0.0784 | 0.0000 | 0.0000 | 0.5606 | 0.0000 |
| 11 | 0.1224 | 0.2979 | 0.0000 | 0.0000 | 0.0924 |
| Residual | 0.4386 | 0.0031 | 0.8872 | 0.4394 | 0.5351 |
| H = 2.4025 QRF | | 1.0242 | 0.9672 | 1.0360 | 0.9864 |

# APPENDIXES

## APPENDIX A
## A DESCRIPTION OF GRADE OF MEMBERSHIP

The Grade of Membership (GOM) model is a pattern recognition technique. It is based on a kind of grouping theory called "fuzzy set" classification. Most grouping techniques create groups where an individual is a member of group one or group two or group three, etc.. Groups of this type are called fixed boundary groups. For example, the AAPCC risk categories used by HCFA are fixed boundary categories--an individual is in a certain age range, is or is not institutionalized or on welfare, is male or female. AAPCC groups are formed by cross classification using all of the AAPCC variables. Thus, one such AAPCC group would be institutionalized sixty-five year old males not on welfare located in a particular county.

GOM is different from conventional fixed boundary groups in four important ways. First, GOM's groups are more like pure types or archetypes than actual groups. We may find, for example, that one pure type is old, has several diagnoses, was probably hospitalized during the year, and is very costly to treat. In the following notation, the number of pure types is denoted as K. Second, each individual is allowed to belong to more than one pure type. In other words, an individual will be assigned a grade of membership in several pure type groups, e.g., 25% pure type one, 30% pure type two and 45% pure type three. The grade of membership for an individual "i" in pure type "K" is written "$g_{ik}$." These scores will later be used to compute prices for the pure type groups. The third important way that GOM differs from other grouping techniques is that it is based on maximum likelihood statistics. This means that its groups are statistically valid, and implies that one may generalize from a sample to the population with little loss of information (shrinkage). (In this analysis shrinkage was less than two percent). Fourth, GOM statistics can be used to determine the appropriate number of groups--a serious problem for other grouping techniques. This property is described in the following more technical discussion of GOM.

"Fuzzy set" classification involves both the notion of logically distinct classes of objects along with the concept of a 'graded' response or degree of membership in those categories. A classification which involves both components can obviously be more flexible and effective in its representation of the real complexity and heterogeneity of individuals. With such a classification system we can generalize our adjustment of the capitation payment amounts to reflect continuous graduations in individuals on a multidimensional basis by identifying discrete dimensions of individual types and using blending or mixing coefficients to generate a weighted composite capitation rate adjustment.

An approach based upon a "fuzzy set" classification procedure will avoid the boundaries problem; the error in categorization generated by forcing things that vary continuously along multiple dimensions into discrete categories.

The Grade of Membership model was originally developed to identify clinically meaningful patient subgroups based upon a large number of symptoms and clinical signs (Woodbury and Manton, 1982) by using the "fuzzy set" approach to categorization. Its utility as a general pattern recognition model (Bezdek, 1982) has been demonstrated in its application to a wide variety of survey and administrative records (e.g., Manton et al., 1984; Manton and Vertrees, 1984; Blazer et al., 1983; Siegler et al., 1984).

In this section we describe the "Grade of Membership" model (Woodbury and Manton, 1982). The purpose of this procedure is to simultaneously identify a.) multivariate relations among sets of variables and b.) the subgroups for which those profiles are characteristic. Thus this procedure is most useful in tasks requiring 1.) the identification of target groups for specific packages of services (e.g., Manton and Vertrees, 1984; Manton et al., 1984; Manton, 1985) or 2.) for identifying risk "sets" or "categories" to adjust actuarial, prospective reimbursement formulas for complex differences in health status. It is also extremely useful in assessing the reliability and validity of sets of measurements.

We present the basic equations of the GOM model by defining four quantities. The first quantity is $x_{ijl}$. The $x_{ijl}$ are the binary variables (i.e., variables which adopt the value of 0 or 1). The data are transformed into these binary variables by coding a 1 for the lth attribute on the jth variable that is possessed by the ith practice. For example, the lth attribute might be "service is available" for the variable "x-ray." Alternatively, the attribute could be a proportion persons with a particular diagnosis or type of medical practice. This type of binary coding is useful because it requires no assumptions about the scaling of responses. Continuous variables can easily be included in the model by coding them into as many response levels as needed to approximate the actual distribution of responses.

The second value we need to define the number of subgroups or types that the GOM program is asked to identify in the data denoted as "K." The value of K is set externally on the basis of theoretical information and is a parameter fed into the program.

The third factor to be defined is $\lambda_{kjl}$. These represent the probability distribution of $L_j$ responses for the jth variable for the kth group. The set of $\lambda_{kjl}$ for the kth analytically-defined subgroup defines the profile of attributes expected for practices of the kth type. Thus, these coefficients perform a role similar to "factor loadings" (i.e., the correlation of the observed variables to the analytically defined factors).

The fourth quantity in the model is $g_{ik}$. The $g_{ik}$'s are coefficients that relate the observed responses for the ith practice (i.e., $x_{ijl}$) to each of the K groups. Thus, the $g_{ik}$ coefficients (GOM scores) are analogous to factor scores in factor analysis with certain important differences. One difference is that the $g_{ik}$'s must be positive (i.e., $g_{ik} > 0.0$) and must sum to 1.0 (i.e., $\sum_k g_{ik} = 1.0$). Also, because they are included directly in the likelihood function, the statistical model on which GOM is based requires no assumption about the distribution of GOM scores ($g_{ik}$'s) over cases. Even in factor analyses where the responses are allowed to be discrete, it is assumed that the underlying factors are normally distributed (Mather and Christofferman, 1981). No comparable assumption is required in GOM. The constraints on the $g_{ik}$'s also imply another important feature unique to the GOM model. That is, since the $g_{ik}$'s for a practice sum to one, they define the observed properties of the practice as a convex set (i.e., a weighted combination) of the properties of each of the K subgroups. This means that any given practice may be described as a combination of two or more types (i.e., that a practice is not discretely categorized into only one group). This means that with the $\lambda_{kjl}$ and $g_{ik}$'s we can classify physician practices using both discrete (i.e., the K subtypes) and continuous (i.e., the $g_{ik}$) components. The $g_{ik}$ can be viewed as representing residual heterogeneity within each category.

The ability to systematically represent individual heterogeneity within a classification scheme that can be used as the basis to set reimbursement is important for several reasons. First, classification into discrete classes creates a problem for individual units on or near the boundary of two groups. Second, forming a reimbursement system on the basis of discrete, homogeneous price groups often leads to large numbers of groups. The large number is needed to adequately capture the complexities of the current health care system. The GOM model can deal with this additional complexity by using the $g_{ik}$'s in the "blended" rate strategy we describe below.

With the above definitions we may write the basic GOM model as:

$$\text{(II)} \qquad \hat{x}_{ijl} = \sum_k g_{ik} \lambda_{kjl}$$

We see that the predicted value $\hat{x}_{ijl}$ which represents the probability that a physician possesses the lth attribute for variable J is a weighted combination of the $\lambda_{kjl}$'s. When the physician is exactly in the kth group (i.e., $g_{ik} = 1.0$; only one $g_{ik} = 1.0$ and all others must then equal 0.0), his expected response probability will be exactly the $_{kjl}$'s for that group.

Estimation of the two sets of coefficients is conducted by maximum likelihood procedures. That is, the set of $g_{ik}$ and ${}_{kjl}$s that maximize the following likelihood function are found by Newton-Raphson procedures with Kuhn-Tucker constraints on the coefficients (Woodbury and Clive, 1977).

$$L = \prod_{i} \prod_{j} \prod_{l} \sum_{k} g_{ik}\lambda_{kjl})^{xijl} \qquad (12)$$

This is the conditional multinomial likelihood form of the model. An asymptotically equivalent (in terms of parameter estimates) unconditional Poisson likelihood function can also be used which is computationally simpler.

With the above equations we can see that the GOM model has certain important statistical properties. First of all, it deals appropriately with missing data. Specifically, if we do not observe a response on the jth variable, all $L_j$ of those binary responses will be equal to 0. This means that all exponents $x_{ijl}$ for that variable for that physician will be 0. Taking the log of the likelihood function, we see that such terms do not change the likelihood value.

Second, we see that the likelihood approach provides an objective procedure for testing the appropriate order of the model (i.e., determining the correct value of K). This is done by observing that the increase in the likelihood function when one goes from K to K+1 groups is distributed approximately as one-half chi-square, with the degrees of freedom equal to the difference in the number of $g_{ik}$'s and ${}_{kjl}$'s for the K and K+1 cases.

Third, since the distributional parameters $g_{ik}$ are estimated in the likelihood, we make no assumption about their distribution over cases. Fourth, because the $\lambda_{kjl}$ are exterior points (i.e., $g_{ik}$ can never be greater than 1.0 so that the observed points $x_{ijl}$ must always be in the space bounded by the set of $\lambda_{kjl}$) we can obtain the same values for $\lambda_{kjl}$ even if the sample changes--even if that change is systematic. That is, the $g_{ik}$'s can absorb a considerable degree of sampling variability so that the $\lambda_{kjl}$'s can be relatively robust to sample difference. For example, on of the sets of $\lambda_{kjl}$'s may define a profile of a range of attributes associated with a specialty. However, a physician who has many of these attributes, the probability of being observed in the community may be low. In this case we may still identify the appropriate set of $\lambda_{kjl}$ by using several data sources.

Fifth, we can now see why we can analyze very complex profiles eve when the number of cases is small. This is because the number of pieces of information (i.e., the number of elements i, j, l in equation 2) increases as the number of variables and responses increases--as well as when the number of cases increases. Indeed, the asymptotic properties of the $g_{ik}$ and $\lambda_{kjl}$'s can be worked out in terms of the increase of information when both the number of cases (for the $\lambda_{kjl}$'s) and the number of variables (for the $g_{ik}$'s) goes to infinity (Tolley, et al., 1985).

In addition to the statistical properties, the GOM model has other mathematical properties that make it useful. For example, in any GOM analysis, we can separate variables into an "internal" set and "external" set. Internal variables are those for which the calculation of the $\lambda_{kjl}$'s affects the likelihood value (i.e., equation 12) and derivatively affects the values of the $g_{ik}$s. Thus, internal variables may be viewed as defining the K groups. External variables are included in the likelihood calculations (so we obtain the optimized value of $\lambda_{kjl}$), but they are not allowed to affect the likelihood function value. Since they do not affect the likelihood value, they do not affect the value of the $g_{ik}$'s. The information content of the external variables does not affect the subgroup definition. Because of this independence, the $\lambda_{kjl}$'s for the external variables provide a way of measuring the external validity or reliability of the internal variables. For example, if we had two sets of measurements of a common phenomenon, we could use one set as internal and one set as external. We would then wish to determine whether the profile of $\lambda_{kjl}$'s for the internal and external variables on the same type (i.e., for the same value of K) are similar. Alternatively, we could assess whether a set of measurements had predictive validity. In this research we use this property to assess the value of additional information. This is done by adding response variables in two sets to a base set of information. Specifically, we begin with five variables describing practice type, then add fourteen variables related to service availability, then add twenty-one diagnostic variables.

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